AN INTEGRATIVE ASSESSMENT OF THE COMMERCIAL AIR TRANSPORTATION SYSTEM VIA ADAPTIVE AGENTS

A Dissertation
Presented to
The Academic Faculty

by

Choon Giap Lim

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

School of Aerospace Engineering
Georgia Institute of Technology
December 2008

AN INTEGRATIVE ASSESSMENT OF THE COMMERCIAL AIR TRANSPORTATION SYSTEM VIA ADAPTIVE AGENTS

Approved by:

Dr. Dimitri N. Mavris, Advisor
School of Aerospace Engineering
Georgia Institute of Technology

Dr. Jung-Ho Lewe
School of Aerospace Engineering
Georgia Institute of Technology

Dr. Hojong Baik
Department of Civil, Architectural and Environmental Engineering
Missouri University of Science and Technology

Dr. Daniel Schrage
School of Aerospace Engineering
Georgia Institute of Technology

Mr. Kurt Neitzke
Langley Research Center
National Aeronautics and Space Administration (NASA)

Date Approved: August 22, 2008

To my family, for their love,

patience, and unwavering support

ACKNOWLEDGEMENTS

I would like to extend thanks to my adviser, Dr. Dimitri Mavris, who has provided invaluable advice, encouragement, and support throughout the years. To Dr. Jung-Ho Lewe, for his guidance in the research work for this dissertation. To Mr. Kurt Neitzke, Dr. Hojong Baik, and Dr. Daniel Schrage, for sharing their wealth of knowledge. To Dr. Daniel DeLaurentis and Dr. Elena Garcia for their mentorship during my early years at Georgia Tech.

I would like to also thank my friends, Eunsuk, Timothy, Xin Yuan, and Joseph, who have helped carry me along in this journey, shared with me their knowledge and most importantly their friendship.

Most importantly, I owe what I have achieved today to the unwavering support from my parents, Victor and Anne, who have given me the inspiration and confidence from the very beginning and continued to support me till the end. To my siblings, Harry, Joyce, and Melody, who have paved the early paths for me to get here. Last but certainly not least, to my wife, Katherine, who has been there with me through the highs and the lows.

Thank you all.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS OR ABBREVIATIONS

α	Advance purchase period.
β_i	Richards growth function parameters.
δ	Fare bucket.
ϕ	Hubbing ratio.
π_{ij}	1995 ATS true origin-destination demand.
$\tau_{ij,av}$	True aviation origin-destination demand.
$\triangle\{\}$	Triangular distribution.
A_j	Total attracted trips.
C_i	Clustering coefficient.
d	Node order degree.
DOC	Direct Operating Cost.
E	Edge.
$ETOC_{pax}^{s_i}$	Expected TOC per passenger on segment flight s_i.
F_{freq}	Flight frequency weighted cost function.
F_{traj}	Flight trajectory weighted cost function.
$FARE_{base}^{R}$	Base fare per passenger on route R.
$fracCE$	Connecting to total enplanement ratio.
IOC	Indirect Operating Cost.
IOC_a	Indirect Operating Cost per departure.
IOC_b	Indirect Operating Cost per passenger.
$P_c(R_{a\rightarrow b})$	Connecting probability of route connecting a and b.

P_i Total produced trips.

$p_{\alpha,\delta}$ Perceived demand function probability.

R Agent displacement boundary radius.

TOC Total Operating Cost.

TOC_{pax}^{R} TOC per passenger on route R.

U Utility function.

V Vertex.

ABM/S Agent-Based Modeling & Simulation.

ACES Airspace Concepts Evaluation System.

ASDI Aircraft Situation Display to Industry.

ASM Available Seat Mile.

ATM Air Traffic Management.

ATS American Travel Survey.

BADA Basic Aircraft Data.

BTS Bureau of Transportation Statistics.

CAS Complex Adaptive System.

CATS Commercial Air Transportation System.

CDF Cumulative Distribution Function.

CER Cost Estimating Relationship.

CONUS Continental United States.

DB1B Airline Origin and Destination Survey.

EMSR Expected Marginal Seat Revenue.

ETMS Enhanced Traffic Management System.

FAA Federal Aviation Administration.

FAM Fleet Assignment Model.

HHI Herfindahl-Hirschman Index.

ILP Integer Linear Programming.

JPDO Joint Planning & Development Office.

LCC Low Cost Carrier.

LF Load Factor.

LGC Legacy Carrier.

MAS Multi-Agent System.

MCATS Monte Carlo Air Taxi Simulator.

MCS Monte Carlo Simulation.

Mi Mi Model.

MIP Mixed Integer Programming.

MNL Multinomial Logit.

MSA Metropolitan Statistical Area.

NAS National Airspace System.

NASA National Aeronautics and Space Administration.

NFDC National Flight Data Center.

NOAA National Oceanic and Atmospheric Administration.

NPIAS National Plan of Integrated Airport System.

NTS National Transportation System.

O-D Origin-Destination.

OAG Official Airline Guide.

OPSNET Operations Network.

RASM Revenue per ASM.

RL Reinforcement Learning.

RMS Revenue Management System.

RPM Revenue Passenger Mile.

RUC Rapid Update Cycle.

SATS Small Aircraft Transportation System.

sDB1B Modified Symmetric DB1B.

SoS System-of-Systems.

T-100 Form 41 Traffic.

TransNet Transportation Network.

TSAM Transportation System Analysis Model.

YoY Year-over-Year.

SUMMARY

The overarching research objective is to address the tightly-coupled interactions between the demand-side and supply-side components of the United States Commercial Air Transportation System (CATS) in a time-variant environment. A system-of-system perspective is adopted, where the scope is extended beyond the National Airspace System (NAS) level to the National Transportation System (NTS) level to capture the intermodal and multimodal relationships between the NTS stakeholders. The Agent-Based Modeling and Simulation technique is employed where the NTS/NAS is treated as an integrated Multi-Agent System comprising of consumer and service provider agents, representing the demand-side and supply-side components respectively. Successful calibration and validation of both model components against the observable real world data resulted in a CATS simulation tool where the aviation demand is estimated from socioeconomic and demographic properties of the population instead of merely based on enplanement growth multipliers. This valuable achievement enabled a 20-year outlook simulation study to investigate the implications of a global fuel price hike on the airline industry and the U.S. CATS at large. Simulation outcomes revealed insights into the airline competitive behaviors and the subsequent responses from transportation consumers.

CHAPTER I

INTRODUCTION

1.1 *The Evolving Commercial Air Transportation System*

The United States Commercial Air Transportation System (CATS) was originally spearheaded by the transport of air cargo, beginning in the 1920s. In the past 80 years, the system has evolved over time and through the many past events, namely, the two World Wars, the debut of jet engines, the Deregulation Act, the Airbus-Boeing rivalry, airline economic crisis, and the rising fuel price. One of the most notable evolution is that while air cargo transportation continues to play a key role in economic and trade expansions, commercial passenger air travel has emerged as the key player in the present CATS. In 2005, the total number of passenger jet aircrafts flown by U.S. carriers is approximately four times that of cargo jet aircrafts (Federal Aviation Administration, 2006a). In addition, the total revenue passenger enplanements for domestic commercial passenger air travel makes up more than 90 percent of the total revenue passenger enplanements.

Another prominent outcome of evolution in the modern era of aviation is the emergence of the hub-and-spokes air transportation network. After the Deregulation Act was passed in 1978, the competition between airlines intensified to the point that airlines intrinsically learnt to streamline their operations by operating from hub airports. Borenstein (1992) and Bamberger and Carlton (2003) reported an overall increase in the concentration of air traffic at hub airports from 1977 to the early 1990s. Within the thirty years after Deregulation, the industry has seen the conglomeration of the airline industry, leading to the conceptualization of the currently observed Big Six network or legacy carriers, namely, American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, United Airlines, and US Airways.

The U.S. airline industry started to show a downturn in the late 1990s and lost serious momentum at the turn of the millennium. In the six year period since 2000, American carriers have lost approximately $40 billion, contributed mostly by the Big Six (Reed, 2006). Some of the internal factors attributed for these losses are the high cost structure of these network carriers (largely due to the labor contracts), complicated fare structure, poor customer service, and inept leadership at these airlines. Meanwhile, the primary external factor leading to this crisis is the intense price wars by the low cost carriers. One of the fallout of the unregulated and competitive marketplace is the strong rise of low cost carriers particularly Southwest Airlines. Table 1 shows that the total market share of domestic origin and destination passengers in the U.S. owned by low cost carriers tripled from seven percent in 1990 to over twenty percent in 2002. These carriers grew rapidly and are capable of embarking in price competitions with the larger carriers by offering simple products, positioning for profitable markets, and maintaining low operating costs.

The industry took its biggest blow in the event of September 11$^{\text{th}}$, which caused air travel demand to drop by almost seven percent in 2001. In the attempt to restructure, four of the Big Six had filed for Chapter 11 bankruptcy: United (2002), US Airways (2002), Delta (2005), and Northwest (2005). One of the key restructuring strategies is to cut back on the operations of unprofitable fleets and flights. The Big Six as a whole have reduced the number of operating fleet by 21 percent from 3,469 in the end

Table 1: U.S. Air Carriers Percentage O-D Passenger Share, 1990-2002 [Adapted from Ito (2003, p. 4)]

Carriers	1990	1992	1994	1996	1998	2000	2002
AirTran			0.6	1.0	1.2	1.5	1.9
ATA	0.1	0.1	0.7	0.9	1.1	1.3	1.9
JetBlue						0.3	1.3
SouthWest	7.0	9.6	12.7	14.1	13.8	14.9	15.8
Other low cost carriers		0.2	2.4	3.1	2.5	2.6	2.8
Total low cost carriers	7.1	10.0	16.3	19.0	18.5	20.6	23.7
American	14.8	16.2	12.7	11.0	10.8	10.9	14.1
Continental	6.8	7.4	8.3	6.5	7.0	6.7	6.8
Delta	12.6	15.5	14.8	14.8	16.2	16.1	16.0
Northwest	7.1	7.5	7.1	7.5	7.0	7.6	7.6
United	11.5	12.7	11.2	11.9	13.2	11.7	10.2
US Airways	14.0	12.4	12.3	10.1	10.7	10.4	9.6
Total Big Six carriers	69.8	71.6	66.5	61.9	64.7	63.4	64.2
Other carriers	26.1	18.4	17.2	19.1	16.8	16.0	12.1
Total carriers	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

of 2000 to 2,747 in 2005 (Perez and Trottman, 2006). The National Airspace System (NAS) domestic capacity is expected to decline for the first time after showing a steady comeback for the past few years since the big dip in 2001. Rigorous efforts have also been carried out to renegotiate new labor contracts that would ease the financial burden of these incumbent carriers.

The dramatic changes in the airline industry have shown that both the network structure and the economic wellbeing of the CATS are heavily influenced by the competitive market forces in place. The impact of these market forces on the different airline business models should be considered in studying the evolution of the CATS and be conducted in a *time variant environment*. Any attempts to assume otherwise with the intent of looking only at the end-states will lose details in understanding the evolutionary processes within the system. This is because the problem at hand is path-dependent and poses several volatilities that are specific to the CATS, one of which is that the NAS problem is a highly complex problem, where one can easily lose direction and focus of the research if the scope and boundaries of the problem are not properly defined. A properly defined scope and boundary should be attained in order to yield a methodology/framework that will capture the key elements of the problem without losing the fidelity level necessary for making meaningful reasoning out of the model. Besides that, forecasting travel demand in the presence of new aviation concepts particularly new airline business models becomes more than just applying growth factors to baseline travel demand. The air travel demand and the NAS capacity becomes tightly coupled in this evolutionary process of balancing demand and supply, where decisions made by airlines will affect air travel demand over time and vice versa. Hence, the pivotal premise and key motivation for this research is to understand and to model the CATS as a *living system*; a system that possesses sentient behavior[1] and evolves in the presence of both spatial and temporal perturbations within the system.

1.2 Research Statement

The discussions so far are intended to reveal the pressing matters within the NAS and that there is a need to better understand the air transportation system as a whole in order to address those matters. The NASA Aeronautics Blueprint published in 2002 clearly acknowledged that "the aviation system is a system of systems" and that "the interrelationship of the many systems that make up aviation evolved throughout the 20th century (NASA, 2002)." An in-depth survey by the Aeronautics and Space Engineering Board at the National Research Council (2006) further reinforced the idea

[1]Sentient behavior can be defined as the condition or quality of being conscious and aware of its environment and other entities sharing the environment.

that "the air transportation system must be understood as a complex interactive system, because its performance emerges from collective interactions among many independent systems and organization." Classifying the air transportation system as a SoS is the first step for clarifying the problem statement, where the objectives and focal points of the research can now be presented.

The ultimate purpose of this research is to craft one building block for the NASA's bold goal as stated in the Aeronautics Blueprint, that is, the construction of "complex, intricate and comprehensive system models" that are required for analyzing the aviation SoS (NASA, 2002). Being that the aviation SoS is a large, complex problem, attempts to provide an all encompassing solution by emphasizing all aspects of the problem is futile. Key focal points aimed at answering and understanding key research areas within the aviation SoS must be identified. As a first step towards identifying these key focal points and research areas, the aviation SoS is decomposed as a broad collection of demand-side and supply-side component systems. These component systems are derived from entities that are directly involved in the commercial aviation industry, as shown in Figure 1.

Table 2 shows that domestic enplanements accounted for the large majority of the total enplanements in the U.S. Thus, in the interest of narrowing the boundary of this study, this thesis emphasized only on the *domestic commercial passenger air travel* within the United States.

Looking at Figure 1 and recalling the discussions on the evolving NTS presented earlier, the issues of capacity constraints and network disruptions leading to air travel delays have always been a concern for all air transportation stakeholders. Naturally, most air transportation research in the past half a century focused on capacity and air traffic management impediments, creating models to assess infrastructural and ATM innovations. While these supply-side components are essential to the system's

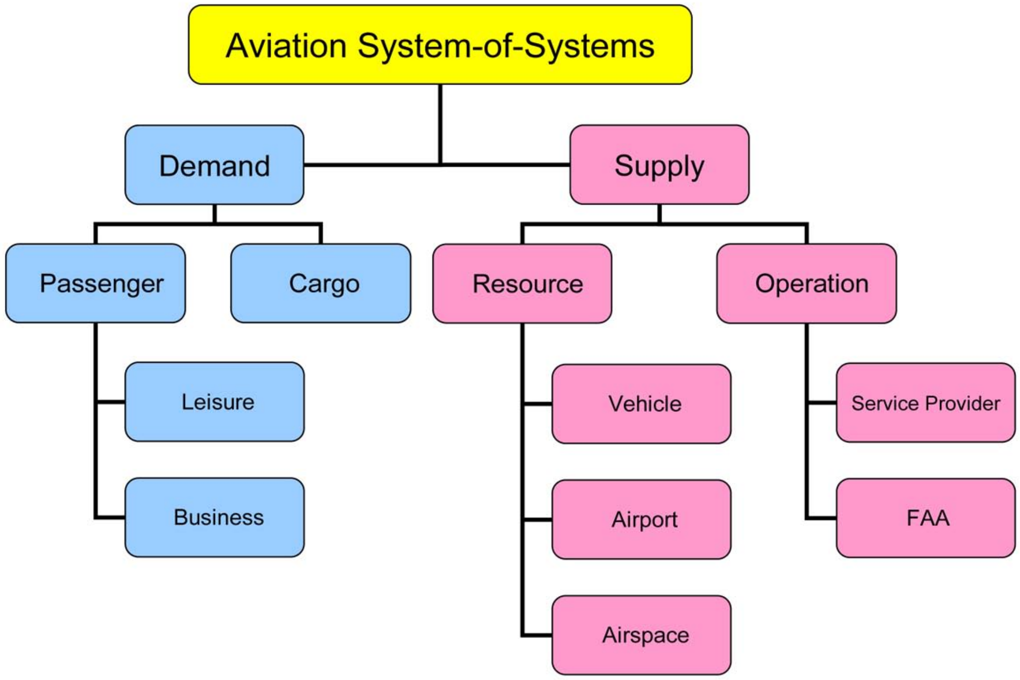


Figure 1: Demand-Supply Decomposition of the Aviation System-of-Systems

Table 2: U.S. Air Carriers Revenue Passenger Enplanements (in millions), 2000-2005 [Source: FAA (2006)]

Year	System Total	Domestic	% Domestic	International	% International
2000	697.6	641.2	91.9%	56.4	8.1%
2001	683.4	626.8	91.7%	56.7	8.3%
2002	625.8	574.5	91.8%	51.2	8.2%
2003	642.0	587.8	91.6%	54.2	8.4%
2004	689.9	628.5	91.1%	61.4	8.9%
2005	738.6	669.8	90.7%	68.8	9.3%

operations, there is a need to concurrently consider the other side of the equation, namely, the air travel demand that created the infrastructural needs in the first place.

With this additional demand-side perspective, it is possible to think of the larger picture when studying the aviation SoS. For instance, the demise of the Concorde is largely attributed to the lack of considerations for market-related factors, albeit being one of the technological marvels of modern times. Also, studying the elements of evolution within the aviation SoS mandates the consideration of time variance. Based on all the aforementioned motivational observations and research thrusts, the overarching objective for this research is to address the tightly-woven interactions between demand-side and supply-side components of the aviation SoS in a time-variant environment.

1.3 Thesis Organization

The motivation and research statement for this thesis has been discussed so far. The remaining discussions of this thesis is organized in the structure shown in Figure 2. Chapter II reviews the literature on existing air transportation research work from the demand- and supply-side perspectives. Details of the aviation models and databases reviewed are provided in Appendix A. Chapter III presents solution approaches for addressing the three key ingredients for modeling transportation systems in the context of this research, namely, complex systems, transportation environment, and demand-supply interactions. Details of the Agent-Based Modeling and Simulation and network modeling techniques are provided in Appendix B and C respectively. Chapter IV presents the implementation steps beginning with an overview of the proposed Modeling & Simulation framework followed by the detailed implementation of the Transportation Environment Model and the Integrative Demand-Supply Model components. Details of the Revenue Management Systems method and Reinforcement

Learning technique are provided in Appendix D and E respectively. Decile income distributions data for modeling the economic profile of consumer agents are provided in Appendix F. Chapter V presents the calibration efforts for verifying and validating the proposed model and methodology. Chapter VI presents a simulation study that investigates two different scenarios. Lastly, Chapter VII presents the concluding remarks of the thesis along with recommendations for future work.

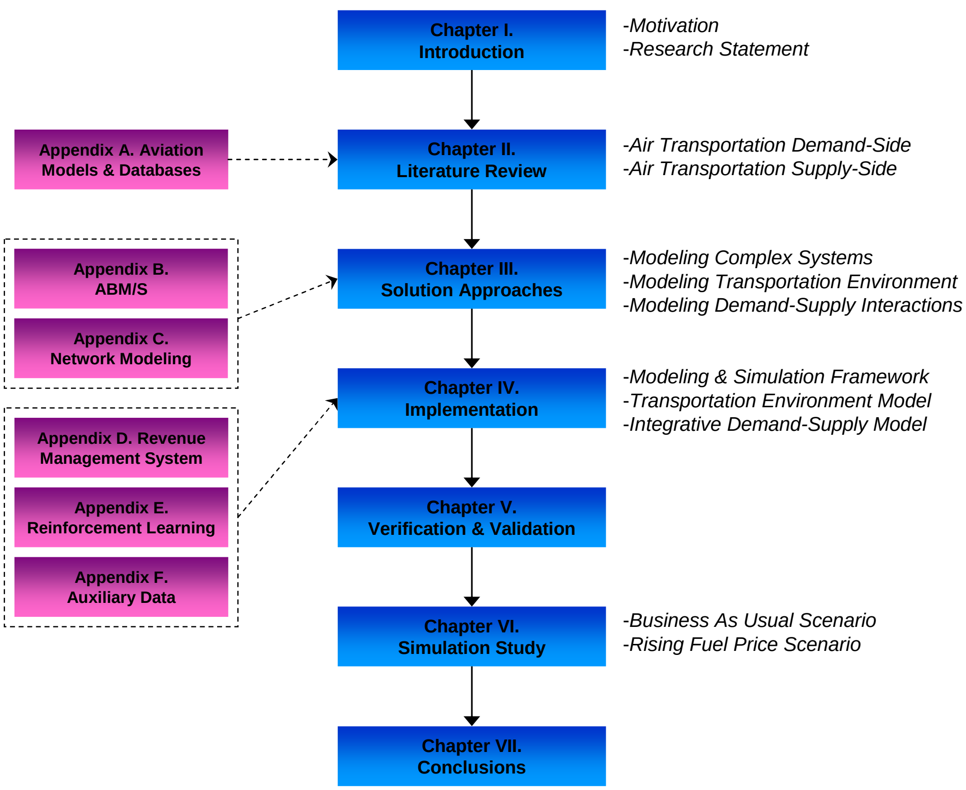


Figure 2: Thesis Organizational Structure

CHAPTER II

LITERATURE REVIEW

Literature review of background materials related to this transportation system-of-system research is documented in this chapter. A discussion on the intermodal and multimodal relationships that exist between key stakeholders of the National Transportation System (NTS) is first provided. Clearly, the National Airspace System (NAS) is a subset of the NTS. This thesis postulates that in order to capture these crucial relationships, the aviation SoS research scope must extend beyond the NAS level into the NTS level.

Commercial air transportation is initiated when travelers purchase air travel services from air service providers. The transactions are executed by employing air vehicles, airport infrastructures, and air traffic control infrastructures. Thus, the air transportation demand-side components are discussed through a survey of existing research and modeling efforts related to travel demand forecasts at both the NAS and the NTS levels (Section 2.1). The air transportation supply-side components are discussed next through a survey of existing research and modeling efforts related to the NAS infrastructure and the air service providers (Section 2.2). This research is refrained from dwelling into in-depth discussions and modeling of non-aviation transportation providers so that the research boundaries can be kept within the domains of aviation research. An interim summary is provided for both the demand-side and supply-side components. In closure, several key findings identified from the literature review process are discussed at length (Section 2.3). The acronyms and descriptions of databases used by the reviewed models are elaborated in Appendix A.7.

2.1 Air Transportation Demand-Side Components

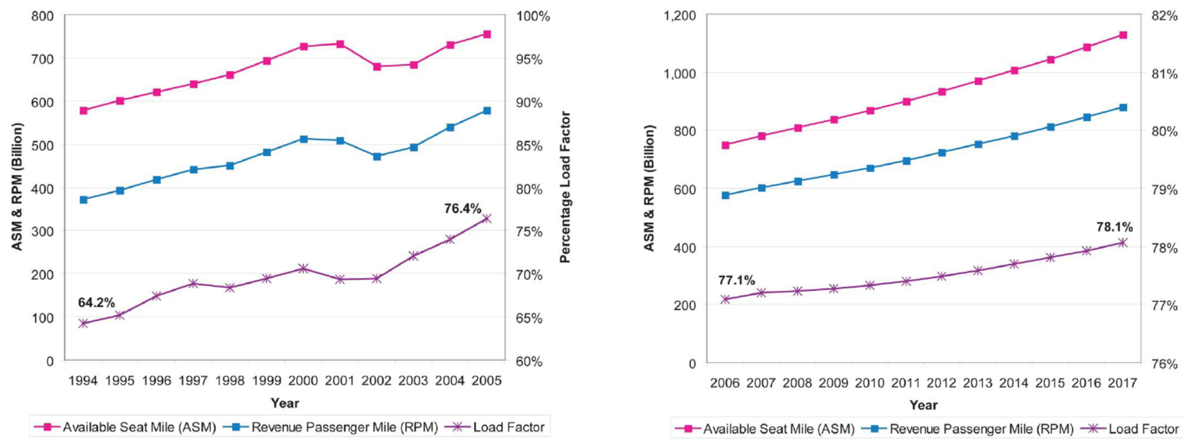
2.1.1 Aviation Demand Forecasting Methodology

The NAS passenger demand refers to the passenger travel demand by means of civil aviation, whether commercial or private. The NAS domestic capacity measured by Available Seat Mile (ASM)[1] and the domestic passenger air travel demand measured by Revenue Passenger Mile (RPM)[2] have experienced average annual growths of 2.5 percent and 4.2 percent respectively from 1994 to 2005. One of the key implications observed is that the NAS capacity is growing at an average of 1.7 percent slower than air travel demand every year over the 12-year period. As shown in Figure 3a, the closing gap between air travel demand and the NAS capacity is directly translated to an over 12 percent increase in load factor from 64.2 percent in 1994 to 76.4 percent in 2005 (Federal Aviation Administration, 2006b). From a financial perspective, airlines would want to maximize load factor since it contributes to revenue gains. However, when a certain threshold load factor is surpassed, service levels begin to fall due to overcrowding at the terminals. Declining customer satisfaction and loss of goodwill will in turn create economic losses to the airlines. More critically, if the aforementioned growth rate trend continues, the current capacity surplus will certainly be depleted. This closing gap is indeed the Achilles heel for both public and

[1] An Available Seat Mile is an industry unit measuring one available seat on an aircraft flown for one mile.

[2] A Revenue Passenger Mile is an industry unit measuring one paying passenger flown for one mile.

private institutions alike. Naturally, most air transportation researches in the past half a century focused on capacity and Air Traffic Management (ATM) impediments; creating models to assess infrastructural and ATM innovations.



a) Historical b) Forecast

Figure 3: U.S. Domestic NAS Capacity and Demand [Source: FAA (2006)]

Since the inception of civil aviation, private and public institutions alike have been studying historical aviation data for the purpose of forecasting passenger demand. Fortunately, aviation data such as the ones depicted in Appendix A.7 are abundant. Besides aviation data, other forms of econometric data that are hypothesized as contributing factors for aviation demand growths are also studied. Some of the most common contributing factors are population growths and Gross Domestic Product growths. In general, these forecasts are typically presented only as travel volume counts but sometimes entail detailed flight specifications as well. The most prominent econometric demand forecasts in the industry are provided by Boeing, Airbus, and the FAA. While the exact methodology employed to create these forecasts are typically undisclosed, they consistently serve as the benchmark forecasts for aviation demand studies. For a more detailed forecast, the Federal Aviation Administration (2006b) publishes an Aerospace Forecasts Report annually, which provides forecasts for air transportation related indicators for the next foreseeable 12-year period based on econometric forecast models. It is the FAA's role to push for the realization of the forecasted NAS capacity growths. This can and should be done through a combination of gradual short-term solutions via airline and airport expansions and long-term solutions that aim to restructure the configuration and utilization of the NAS. Figure 3b shows the forecasted domestic commercial passenger air travel demand and NAS capacity.

Several observations can be made from these econometric forecast models. Firstly, albeit demonstrating different outcomes, all the models are derived from resonating methodologies. For example, economic growths play a significant role in the travel demand growths. Urbanization and demographic changes are also cited as influential factors for shifts in travel demand. Secondly, these forecasts are made over a long period of time, typically in excess of 15 years. However, these deterministic forecasts are based on finite assumptions that may very well change in the near term, let alone over a 15-year stretch. Hence, Boeing and the FAA readjust these forecasts almost annually, while Airbus updates its forecast every few years. Lastly, since the internal construct of these forecast models are not publicly disclosed, it is beneficial to investigate simulation-based aviation demand models. Simulation-based aviation demand models generate NAS passenger demand by extrapolating a baseline flight demand set to future values via hypothetical demand growth factors. One of the most recent and representative demand forecast simulation model is AvDemand (Huang et al., 2004), created by Sensis Corporation for NASA to provide NAS traffic demand predictions for evaluating futuristic and advanced concepts. The model possesses an application library database that compiles existing data for airports, aircraft, airspace, waypoints, geographic and demographic profiles. AvDemand adopts a top-down approach for its flight-based demand generation, which assumes a baseline flight demand set and grows the future flight demand sets from that baseline. After generating schedules for these flight demand, the output from this model can then be exported directly into other NAS models. The capabilities and limitations of AvDemand are summarized in Table 3 and a thorough model description is provided in Appendix A.

2.1.2 General Transportation Demand Theory

In lieu with the SoS premise, the scope of air transportation activities should extend beyond the NAS into the NTS. This argument can be rationalized from two forms of foundational relationships between transportation modes: intermodal and multimodal relationships. Quoting the NASA Aeronautics Blueprint once again, "consideration must be given to the intermodal relationships with the larger transportation systems (land and sea) (NASA, 2002)." In a realistic transportation environment, air transportation is part of the travel activities that include ground and maritime transportation. While it is a commonly accepted practice to discard maritime transportation activities, the intermodal and multimodal relationships between the air and ground transportation systems play a crucial role in shaping aviation demand and are discussed next.

In this context, intermodal relationships can be defined as the *reinforcing interactions* between different transportation modes in completing *different trip segments*. For example, a traveler who is planning to take a commercial flight must first employ a ground transportation mode to go from the origin location to the departure airport, and possibly from the arrival airport to the destination location as well. On the other hand, multimodal relationships can be defined as the *competing interactions* between different transportation modes in completing *the same trip segment*. For example, a traveler can choose between commercial air carriers and personal automobile to travel between any two origin and destination locations as longs as the mode options are available.

The presence of intermodal and multimodal relationships have several implications on the transportation activities, particularly in terms of travel demand patterns. Intermodal relationships provide a more accurate and conclusive analysis of a trip by considering all secondary trip segments other than the primary segment, which typically involves a commercial transportation mode. Urbanization and other changes in demographic and lifestyle patterns are injecting more variability in the time and cost components of these secondary trips, causing them to indirectly play a larger role in the overall mode choice selection. Meanwhile, multimodal relationships introduce relative competition in the mode choice selection by pitting transportation modes against one another. According to the U.S. Department of Transportation (1999), the utilization of ground transportation for long distance trips in the Continental United States (CONUS) overwhelms that of air transportation by over three fold. Thus, multimodal relationships provide a more realistic representation of the air travel demand as a subset of the total travel demand that is dominated by ground transportation activities.

The outcome is then a model that projects a more accurate, conclusive, and realistic transportation environment, where higher fidelity and more detailed analyses can be performed. For instance, NAS service providers should think of how to gain and maintain competitive advantage in the presence of the other NTS modes, which can be both competing alternatives as well as reinforcing modes for aviation demand. In summary, intermodal and multimodal relationships should be considered in the aviation SoS research, and these considerations are made possible by extending the problem scope beyond the NAS level into the NTS level.

There are two general modeling approaches used for forecasting transportation demand: the Four Step Model and the agent-based approach. These two approaches are discussed below.

2.1.2.1 The Four Step Model

Transportation demand forecasting studies in the past have commonly adopted the conventional *Four Step Model*, which was conceived from urban transportation planning studies beginning in the 1950s (McNally, 2000). The four steps are i) trip generation, ii) trip distribution, iii) mode selection, and iv) routing (Weiner, 1997; Peterson and Harrington, 2008).

Step 1. Trip generation

Trip generation refers to the development of quantitative estimates of trip frequency (i.e. travel demand) *produced* in explicitly defined locales or zones. Travel demand can be perceived as the derivative of the fundamental human needs for mobility. Hence, trip generation should be derived based on the fundamental properties that tend to describe consumers' lifestyle and propensity to travel such as demographics, socio-economics, and/or land use factors.

Step 2. Trip distribution

Trip distribution involves distribution of the generated trips to the origins and destinations with the final outcome being a zone-to-zone Origin-Destination (O-D) matrix. This step is typically performed by matching the trip attraction and trip impedance factors. Examples of trip attraction factors are number and types of jobs available and local tourism activities. Examples of trip impedance factors are trip distance, travel time and cost, and travel hazards such as war and natural disasters. Some of the most commonly used methods for obtaining these trip distributions are the gravity model and the entropy maximization model, which are discussed in detail next.

The gravity-based model is an extended application of Newton's theory of gravity for illustrating the transportation distribution relationships by emphasizing the attraction and impedance factors at the origin and destination locations. The most direct use of gravity model for trip distribution are population-based and trip-based models, where population and trip frequency replace the objects' masses in the physical form of Newton's theory of gravity.

There have been many variations of this pure form of gravity distribution model, most notably the doubly constrained gravity model. Initially formulated by Taylor, this method postulates that the interactions between any two zones increases with the amount of transportation activities at each zone (attraction factors) but declines with disutility factors such as the time, distance, and cost of traversing from one zone to the other (impedance factors) (Bruton, 1970). The standard from of the doubly constrained gravity model between origin zone i and destination zone j is given by Equation 1.

$$T_{ij} = P_i\left(\frac{A_j F_{ij} K_{ij}}{\sum_{j=1}^{n} A_j F_{ij} K_{ij}}\right) \tag{1}$$

where T_{ij} = Trips produced at i and attracted at j

P_i = Total produced trips at i

A_j = Total attracted trips at j

F_{ij} = Travel cost friction factor

K_{ij} = Calibration parameter

n = Number of zones

The most commonly used cost function is the inverse function of trip distance between zones i and j given by $F_{ij} = \text{Trip Distance}^{-\gamma}$ where γ determines the significance of this cost function. Given the values of P_i and A_j, the calibration parameter K_{ij} can be iteratively solved to within a preset tolerance that determines convergence of the model. Garber and Hoel (2001) presented a good illustration of this model particularly in the computation of the adjusted attraction factor A_{jk} for iteratively solving the calibration parameter K_{ij} over k iterations. Garber further recommends a five percent tolerance between estimated A and the actual A as the convergence criteria for this iteration. The adjusted attraction factor is mathematically expressed as:

$$A_{jk} = \frac{A_j}{C_{j(k-1)}} A_{j(k-1)} \tag{2}$$

where A_{jk} = Adjusted attraction factor for zone j in k^{th} iteration

C_{jk} = Actual attraction factor for zone j in k^{th} iteration

A_j = Desired attraction total for zone j

Step 3. Mode selection

Mode selection selects the mode choice for executing the distributed trips based on the relative *fitness* of available modes. The choice process is typically performed from the foundations of random utility theory, in which consumers are assumed to be rational entities that will always choose the alternative with the highest fitness to maximize its profit. This fitness metric is a numerical representation of favorability or attractiveness of each choice to the individual, which ultimately reflects the individual's decision making behavior. The concept of utility is used to mathematically express fitness, where the perceived utility of the k^{th} alternative, U_k, is given by Bierlaire

(1996) as:

$$U_k = V_k + \varepsilon_k = c_k + \sum_i \beta_i x_i(k) + \varepsilon_k \tag{3}$$

$$\begin{aligned} \text{where } V_k &= \text{systematic utility} \\ x_i(k) &= i\text{th characteristic for alternative } k \\ \beta_i &= \text{weighted importance of } x_i \\ c_k &= \text{specific constant for alternative } k \\ \varepsilon_k &= \text{associated random term for alternative } k \end{aligned}$$

The choice model is derived based on the assumption made on the distribution of the random term ε_k. While the Gaussian law has been conventionally used to describe and analyze human behavior, Bierlaire (1996) further pointed out that the *probit model* derived from the Gaussian law is not analytically solvable and thus, is limited for use with simple models that do not require heavy analytical analysis. Alternatively, the use of *multinomial logit models* is recommended, where the likelihood or probability of selecting the k^{th} alternative over the remaining choices and are mutually exclusive as given by:

$$Prob_k = \frac{e^{V_k}}{\sum_{j=1}^{n} e^{V_j}} \tag{4}$$

$$\text{where } n = \text{number of mode choices} \tag{5}$$

Step 4. Route selection

Route selection assigns routes or mode-specific networks for the trips based on the selected mode choices. Depending on the type of transportation research performed, routing may be as simple as assigning an straight line trajectory through the origin and destination or it may involve complicated assignment of network paths.

2.1.2.2 Agent-Based Transportation Demand Modeling

The agent-based transportation demand modeling technique was presented by Lewe (2005) and can be perceived as a computational replication of individual transportation consumers with their specific travel profiles and decision-making behaviors being the source of generating transportation demand. As the name suggests, these transportation consumers are represented as agents that are uniquely defined by prescribed geographic, demographic, and socio-economic properties. General decision-making properties can also be instilled to characterize the mode choice selection tendency of the agents.

So far, elements of the Four Step Model have already been brought up in the description of this technique. However, this is where the commonality ends, as the agent-based technique employs these common steps at a microscopic level and in a different order of sequence. A consumer agent would generate a large list of desired trip demand, from which only selective trips would be performed due to consumption limits or constraints in the forms of money, time, and psychological factors. This consumption limit is coined the *mobility budget space concept* with the primary goal of capturing the travel behaviors of consumers by exerting rational and resource limits on their abilities to fulfill trip demand. To better describe the concept, let's assume that a particular consumer desires 12 trips in a year. As each trip is executed chronologically, the consumer keeps record of the cumulative amount of resources expensed. The consumer will continue to fulfill the desired trip demand until the cumulative resources exceeds a predefined threshold. Figure 5 shows an example of a time- and cost-constrained mobility budget space. B_c and B_t are the thresholds for cost and time respectively. Trips 1 to 6 are successfully executed as they fall within feasible mobility budget space. Under this concept, a trip is feasible if and only if all constraints are satisfied; violation of any one constraint would terminate the trip and all future trips. When the consumer attempts to execute trip 7, the cost constraint is violated. Hence, trip 7 and all remaining prospective trips for this consumer are terminated.

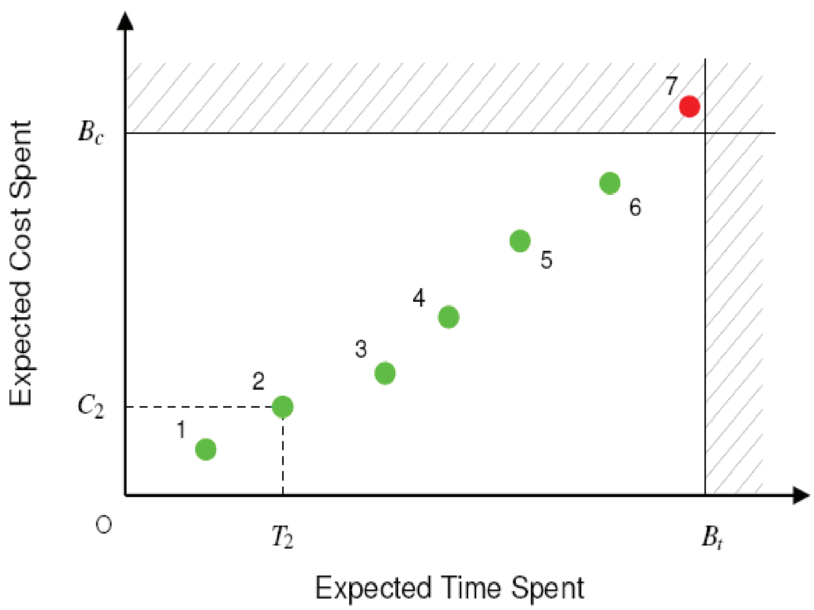


Figure 4: Mobility Budget Space Concept [Source: Lewe (2005)]

Based on the above description, this mobility budget space concept provides a mean of determining the trip frequency of consumer agents as a function of the pre-defined thresholds. An effective way to determine the cost constraint is by computing it as a fraction of the consumers' income, thus, creating independent and unique monetary limits for each consumer. Time constraints can be assumed based on the trip purpose, i.e. the type of consumers involved. The greater benefit of this concept is that the trip frequency has also become a function of the transportation modes employed, where trip frequency will increase as consumers choose more time- and cost-efficient transportation modes and vice versa. This opens up future research opportunities looking into consumer learning and induced demand in the context of the NTS.

2.1.2.3 TSAM & Mi

Numerous travel demand models have been developed in the past. To display the NTS passenger demand forecast methodology, two representative models are briefly discussed in this section, namely, the Transportation Systems Analysis Model (TSAM) and the *Mi* model. These two models are selected because they provide more emphasis on air transportation modes as compared to other existing models. While the goals of the two models are closely aligned, the construction approaches taken are very different. The capabilities and limitations of these two models are summarized in Section 2.1.2.3 and thorough model descriptions are provided in Appendix A.

The Transportation System Analysis Model (Trani, 2006; Trani et al., 2004), is a database-driven simulation model originally developed at Virginia Tech to investigate the viability of NASA's Small Aircraft Transportation System (SATS) program. The primary focus of TSAM is to compute spatially-explicit demand for long distance trips greater than 100 miles (for both business and leisure travel) using socio-economic and demographic data at the 3091 counties in the CONUS. Subsequently, TSAM creates a 3091-by-3091 Origin-Destination (O-D) matrix between these counties, serving as the backbone of this highly detailed transportation demand analysis. The mode choice for the distributed trips are then determined using a multinomial logit model at the aggregated level.

Mi is an agent-based model created at Georgia Tech (Lewe, 2005). It creates a virtual NTS where agents live to imitate the transportation activities within the CONUS as a whole. Two groups of transportation stakeholders are included as the agents, namely, transportation consumers and transportation service providers. The transportation consumers are individuals or groups of individuals producing long distance travel demands, and are populated from either households or enterprises based on the demographic and economic data. The counterparts of the consumers are the transportation service providers that offer price and time information for trips based on the corresponding transportation mode and business model. The CONUS in *Mi* is categorized by generic locales, where all geographic areas under the Census 2000 correspond to one of the four locales: Large-, Medium-, Small-, or Non-metropolitan area. Origins and destinations within each locale share similar characteristics in terms of economic characteristics, accessibility to airports/highway, and other transient factors such as traffic delay. The mode choice for each distributed trip is then determined using a multinomial logit model at the agent level.

Much like the NAS passenger demand, the NTS passenger demand refers to the total passenger travel demand in the CONUS. However, due to the multimodal and large-scale scope of the NTS demand, it is impossible to sample meaningful historical transportation activities data at the national level. One solution for this obstacle is by conducting a national survey on consumer travel. The most conclusive survey for this purpose is the 1995 American Travel Survey (ATS). However, numerous errors and data anomalies were observed in this database as described in Appendix A.7. This calls for careful consideration when using and adapting this database for the modeling process.

Table 3 summarizes the capabilities and limitations of the three demand-centric models reviewed.

Table 3: Capabilities and Limitations of Demand-Centric Models

Models	Capabilities	Limitations
AvDemand NAS level	-Spatially-explicit representation of the CONUS -Detailed flight demand generation and scheduling -Can be integrated with other NAS models -Considers growth models to forecast future demands	-Weak representation of service providers -Does not consider intermodal and multimodal relationships -Cannot capture behavioral aspects of consumer travel -Static annual-based simulation
TSAM NTS level	-Spatially-explicit representation of the CONUS -Considers intermodal and multimodal relationships -Can be integrated with other NAS models -Good visualization	-Weak representation of service providers -Computationally expensive to regenerate scenario changes -No county level data available for calibration -Captures modal split behaviors but only at the aggregated level -Static representative same day simulation
Mi NTS level	-Considers intermodal and multimodal relationships -Captures behavioral aspects of consumer travel -Successfully calibrated against the 1995 ATS data -Entity-centric abstraction framework makes simulation less computationally complicated	-Weak representation of service providers No spatially explicit representation of the CONUS -Static annual-based simulation

2.2 Air Transportation Supply-Side Components

2.2.1 The National Airspace System

The NAS is without question a highly integrative and interactive complex system. Intrinsically, it represents the physical front of the aviation SoS; a swarming sea of moving aircrafts when viewed on a radar screen. Beneath this physical front are two component systems that compose the NAS infrastructure, namely, the airport system and the air traffic control system, which are discussed in Section 3.3.2.1.

The Airspace Concepts Evaluation System (ACES) (Sweet et al., 2002) model is a large scale, agent-based model created by the NASA Ames Research Center under the Virtual Airspace Modeling and Simulation project to reconstruct gate-to-gate actions between key participants within the NAS. This model is the state-of-the-art and most widely-used airspace model by NASA. It performs a non-real-time evaluation of the system-wide NAS in order to assess the costs and benefits of new and revolutionary tools, concepts, and architectures. It is also used by the Joint Planning & Development Office (JPDO) to evaluate the baseline and future scenarios for the NAS (Roth and Miraflor, 2004). The capabilities and limitations of the ACES model are summarized in Section 2.2.2.5 and a thorough model description is provided in Appendix A.3.

2.2.2 Air Service Providers

Air service providers satisfy customers' demand by selling air travel services. An air service provider has to perform several core functions to initiate and to complete a transaction. There have been many research efforts from both the academic and industry domains in trying to model these core functions. There are many notable air service provider models available, especially those that specialize on certain core functions rather than attempting to capture the entire business model. These models invoke specific methodologies and concepts, such as the Revenue Management System (for pricing), network concept (for routing), and mixed-integer linear programming (for routing and fleet assignment).

In reality, air service providers are comprised of multiple functional units; each unit possesses its own core functions, obstacles, and goals. Although driven by profits as the bottomline, these functional units coalesce in a much more complicated and oftentimes intangible way. From an academic research perspective, the air service provider's model can be thoroughly examined based on existing research on four core functions: routing, fleet/frequency selection, pricing, and revenue management. While each function appears independent, they are by no means mutually exclusive when airlines perform their daily operations. For instance, routing is integrated closely with pricing when airlines determine fare levels. In this section, additional emphasis is provided for airline pricing, which serves to be the core area of study for this research. A discussion of each core function and modeling approaches is provided in this chapter. A brief overview of two representative air service provider models, Jet:Wise and Monte Carlo Air Taxi Simulator (MCATS), are also presented.

2.2.2.1 Routing

Ever since the Deregulation Act, there has been a rapid growth in hub airports and subsequently connecting traffic within the NAS. This led to the emergence of the hub-and-spokes networks that best describe the current airline routing structure in the NAS. Morrison and Winston (1989) assessed the overall effects of deregulation and related governmental policy and reported an $14.9 billion of annual benefits (1988 dollars) to the travelers and carriers. Brueckner et al. (1992) studied the concept of increasing load factor by means of consolidating passenger flows through selected airport hubs, while lowering fares in the individual markets. Borenstein (1992) and Bamberger and Carlton (2003) further reported an overall increase in the concentration of air traffic at hub airports from 1977 to the early 1990s via the Herfindahl-Hirschman Index (HHI)[3]. Other studies on the hub-and-spokes network include Berry et al. (1997); Brueckner and Spiller (1994); Caves et al. (1984); Goetz and Sutton (1997); Hendricks et al. (1997). A detailed discussion of the network theory methodology and how it is used to for the commercial air transportation networks are provided in

[3]HHI measures the size of firms relative to the industry size as a means of depicting market competition and concentration.

Appendix C and Section 4.3.2 respectively.

The key question being asked in the context of airline routing is *what is the profitability of operating a certain route?* Research on airline routing has typically been in three main areas: aircraft routing, schedule development, and passenger route choice. Airline routing research employs optimization techniques to determine specific path of an airplane. Schedule development research estimates market sizes and future demand levels in relation to the airline network. Passenger route choice research studies consumers' selection of most favorable routes and itineraries. Mathematical models and optimization techniques are oftentimes used for performing route selections. A commonly used mathematical model is the Fratar algorithm, which grows routes/schedules based on forecasted growth factors and applies the generated routes/schedules onto a given baseline. This method is easy to implement and requires little computational resources. However, it is an aggregated top-down method that is incapable of forecasting route-specific growths. A commonly used optimization model is the Mixed Integer Programming (MIP) model, which determine specific aircraft routes based on a given objective function such as minimizing operating costs and maximizing airline profits. This method can be used to solve for optimal aircraft routes based on any given set of user-specified network properties. However, as the number of variables and network nodes increase, the problem definition tend to increase rapidly as well. Sample applications of the Fratar algorithm and the MIP model on the transportation network problem are demonstrated by Schwab et al. (2000) and Yang and Kornfeld (2003) respectively.

2.2.2.2 Fleet/frequency selection

Fleet selection refers to the specification of the aircraft types for completing a mission. Frequency selection refers to the specification of flight frequencies for completing a mission. In the context of commercial aviation, a mission is typically a given amount of flight demand. Fleet and frequency selections are two processes that are oftentimes interchangeable. In other words, one can choose to specify fleet mix before determining the required frequency for completing a mission or vice versa.

There is a more complicated extension of fleet/frequency selections that includes a flight schedule and an objective function such profit maximization or cost minimization. This extension is coined the Fleet Assignment Model (FAM), which is a string-based aircraft routing model for determining optimal fleet assignments. Along with a specified set of constraints, an optimizer such as the Integer Linear Programming (ILP) model is used to determine the fleet type for each leg of the flight with the objective function as the governing function. While the ILP model is a powerful tool for optimizing aircraft fleet assignments, the mathematical computation for the model is highly complex and requires tremendous amount of computational resources. Sample applications of the FAM are available in Abara (1989); Barnhart et al. (1998, 2002); Rosenberger et al. (2004); Talluri (1996).

2.2.2.3 Pricing

The actual airline booking system is a highly complicated web of publishing and booking nested fare structures with intense human-in-the-loop uncertainties. This system is comprised on two highly interconnected functions: pricing and yield management. The pricing function retrieves air fare values and creates fare classes for the given flight itineraries. Based on these fare classes, yield or revenue management methods are utilized to allocate resources (aircraft seats) for each fare class. Inevitably, there may be conflicting goals between these two functions, since pricing is oriented towards margins and competition but not necessarily towards revenue maximization as advocated by revenue management methods. Hence, optimal pricing requires that these two models remain an integrated function that is coherent with the other operations of air service providers.

Pricing models have been implemented using several methods, one of which is the regression method. Wallenberg performed a multivariate regression on approximately 50,000 fare-flight observations sample from an online travel agency. The variables involved are city-pairs, advanced purchase periods, Saturday night stay-over, and airlines. The goodness of fit was poor based on the low R-squared value of 0.4. Nonetheless, the main finding reported for the study is the rejection of the hypothesis that price is independent of airline price collusion (Wallenberg, 2000). In the modeling of airline agents in the *Mi* model (Appendix A.3), Lewe (2005) collected a much smaller number of observations from an online travel agency and regressed the air fare as a function of trip distance only. On top of that, hypothetical price multipliers are assumed for the different types of consumers, whether they are households or enterprises (with multiple classes based on the size of the enterprise). The regression method is easy to implement and only requires simple polynomial calculations. Regressions methods in general serve well to provide fare estimates for higher level analysis such as modal split analysis.

The cost-based method has also been used for pricing models. This is a much more detailed pricing method that computes the cost of providing air travel services from the individual cost drivers of the service provider. These cost drivers are described by Cost Estimating Relationship (CERs), which are equations and logics that interrelate the individual cost components of a service provider's operations. Summing up these CERs along with a given profit margin allows the model to project a value for the air fare. The MCATS model (Appendix A.6) uses this cost-based pricing method to estimate fares for air taxi services and most of the air taxi CERs are reported by Toniolo and Brindel (2005). The cost-based method is flexible towards design changes and yields the most accurate air fare estimations. However, this would require that the predefined CERs appropriately reflect the cost structures of the air service providers, which in itself is a challenging task. Possible iterative solutions within the nested CERs may also result in longer computation time.

Another method used for pricing models is the data-lookup method. This is one of the most straightforward methods to determine an air fare based on the historical records of air fares quoted for given city pairs. While this entail a fixed pricing based solely on city pairs, one can introduce small adjustment factors based on trip and travelers' attributes. The OAG and the DB1B databases are good sources for using this method. However, these data already accounted for the dynamic pricing actions imposed by the real airlines, which could then cause significant price misrepresentations for the air fares retrieved. The TSAM (Appendix A.2) uses this data-lookup method to estimate air fares for its airline pricing (Trani, 2006). The data-lookup method is easy to implement and requires short computation time. However, depending on the geographic granularity of the model, this method requires a large database of historical fares data. Also, these data need to be pre-processed to treat the fact that dynamic pricing actions by airlines are already taken into account.

2.2.2.4 Revenue Management

Revenue management is a discipline that combines market segment pricing with statistical analysis such that the marginal revenue per unit of available capacity can be increased (Integrated Decisions and Systems, Inc., 2005). Revenue Management System (RMS), also referred to as yield management system, is a dynamic pricing methodology for maximizing the revenues for airlines (Belobaba, 1987; Brooks and Button, 1994; Gallego and van Ryzin, 1994). Bell (2005) further defined revenue management in an intuitive manner as "the science and art of enhancing firm revenue while selling *essentially* the same amount of product."

The engine of RMS is the *discriminative pricing*, made possible through the exploitation of several market segmentation attributes. The most critical ones are origin-destination pair (where and how far to travel), advanced purchase (how long ahead is the purchase before trip is made), connections (how many connecting segments), and seasonality (when to travel). Examples of other attributes are minimum stay, batch size, Saturday night stayover, and ticket refundability. Cross (1997) listed seven core concepts that drives RMS based on this notion of discriminative pricing (See Section D.1). Many of these concepts applied directly to how real world airlines develop their own proprietary methodologies for determining fares. In general, itineraries are grouped into discrete fare buckets based on these attributes. In addition, these fare buckets are constantly changing and are almost always nested, in the sense that itineraries undergo multiple combinatorial groupings of the aforementioned attributes before the final fare can be determined. These market segmentation attributes provide insights that led to the development of the seat inventory control methods; a set of tools that help airlines decide whether to release an additional inventory at a given fare or reserve it for a potential higher fare. An in-depth discussion of RMS along with theoretical foundation of the seat inventory control methods are presented in Appendix D.

Narahari et al. (2005) postulated that there are five modeling approaches for RMS: inventory-based, game theoretic, machine learning, data-driven, and simulation. These modeling approaches are neither mutually exclusive or jointly exhaustive, since most models are data-driven and many are simulation-based regardless of the core concepts utilized. A review of existing RMS research revealed that there are no significant game theoretic models used for RMS. Adapting this finding to Narahari's postulation, the airline dynamic pricing model is then composed of the inventory-based, machine learning, data-driven, and simulation modeling approaches.

The inventory-based approach is the earliest mathematical model used for RMS. With inventory levels as the basis for making pricing decisions, Elmaghraby and Keskinocak (2003) summarized three characteristics of a market environment that deals with inventory:

1. Replenishment versus no-replenishment of inventory
2. Dependent versus independent demand over time
3. Myopic customers (who decide based on current prices) versus strategic customers (who consider future path of prices)

These three characteristics profile the revenue management problem at hand. Subsequently, airline seats are considered non-replenishable, time dependent, and cater to potentially both myopic and strategic customers.

The machine learning approach employs the concepts of machine learning, a methodology for capturing the behavior of learning agents in a scenario where information is limited, thus, forcing these agents to adapt and improve their states. Several RMS models have adopted the machine learning method to create adaptive airline agents capable of locating optimal fares for maximizing profits (Garcia et al., 2005; Gosavi, 2004; Schwind and Wendt, 2002). A more specific technique of machine learning commonly used is Reinforcement Learning, which is discussed in Section E.

The data-driven and simulation approaches have been commonly used by all types of modeling research. The only requirement for the data-driven approach is that appropriate and ample data are available. In the context of airline RMS, customer data are aplenty within the records of airlines and other travel research organizations. These data-driven models are used to provide insights into the customers' purchasing patterns, particularly in terms of the *willingness to pay*. Meanwhile, simulation by itself is merely a method to reconstruct computational representations of a real system with the goal of mimicking its behaviors.

The RMS models used by airlines heavily employ the inventory-based and data-driven approaches. These models have been continuously improved for over 30 years and have become an industry-wide practice. However, the question of modeling feasibility arises when viewing the problem from an academic research perspective since efforts to replicate the actual airline RMS oftentimes become overly complicated when the nested fare structure manifests. Furthermore, an enormous amount of data is required in addition to an industry-wide scope such that the fare class for any given market pair can be appropriately estimated. Belobaba (1987) pointed out that "the size of the seat inventory control problem can become unmanageable. Clearly, no airline is in a position to make separate seat inventory control decisions about each of the tens of thousands of price/product combinations it offers every day." Translating this to a modeling point of view, the traditional RMS via seat inventory control tends to grow out of proportion when a large-scale simulation is involved.

2.2.2.5 Jet:Wise and MCATS

Jet:Wise and MCATS are simulation-based models with the *best attempts* at replicating the all-encompassing air service provider business model. The capabilities and limitations of these two models are summarized in Section 2.2.2.5 and thorough model descriptions are provided in Appendix A.3.

Jet:Wise is an agent-based model created at the MITRE Corporation (Niedringhaus, 2000, 2004). This model explores a NAS marketplace emphasizing the airline operations. To imitate the interactions between the airlines, the NAS infrastructure, and the consumers, Jet:Wise models the economic decisions such as hubs location, fleet selection, scheduling, pricing, and airline reactions (to delays, congestions, and missed connections). It also addresses how airlines' decision-making is influenced by capacity-related events such as allowable airport hourly capacities, weather disruptions, and congestion delays. Jet:Wise simulates iterative cycles of the same virtual day rather than progressively over a simulation timeline. Using information from the previous cycles, the model learns to improve itself until the internal objective function is satisfied.

MCATS is a Monte Carlo Simulation (MCS) model created by RTI International with the emphasis on modeling potential regional air taxi networks and improving NASA's understanding of service providers' cost structures (RTI International, 2006; Toniolo and Brindel, 2005). The model has since been extended to include other SATS-like services such as fractional ownership and self-piloted lease. The primary purpose of the model is to analyze the business strategies for these air service providers by determining both the internal and industry-wide cost drivers. By measuring the financial performance of service providers, the impacts of technological and operational innovations are captured in the form of economic metrics. This section of the literature review surveyed the fundamental construct and modeling approaches for the NAS infrastructure as well as for air service providers. Air service providers are entities with highly complex structure, composed of business units with unique functions, goals, and constraints. The core functions of these service providers, namely, pricing, routing, and fleet/frequency selection, were discussed. Two key observations were made in regard to these core functions. Firstly, it was realized that while the fleet/frequency selection remains to be an important function, it dwells into highly detailed operational activities at the vehicle level which are perceived to be beyond the scope of a nationwide system level study. Secondly, since pricing is typically performed by approximating a base price followed by a more refined price adjustment

Table 4: Capabilities and Limitations of Supply-centric Models

Models	Capabilities	Limitations
ACES NAS level	-Spatially-explicit representation of the U.S. -Detailed modeling of daily NAS operations -Can be integrated with other NAS models	-No representation of service providers -Does not consider intermodal and multimodal relationships -Demand is a fixed input that is unaffected by service providers' actions -Static representative same day simulation
Jet:Wise NAS level	-Spatially-explicit representation of the U.S. -Detailed modeling of airline operations -Captures behavioral aspects of airlines	-Does not consider intermodal and multimodal relationships -Demand is a fixed input that is unaffected by service providers' actions -Static representative same day simulation
MCATS NAS level	-Spatially-explicit representation of the U.S. -Detailed modeling of regional air service providers operations -Allow transient analysis	-Does not consider intermodal and multimodal relationships -Demand is a fixed input that is unaffected by service providers' actions -Cannot capture behavioral aspects of regional air service providers

via the RMS model, the base price model need not be a highly accurate model. The discussion on the RMS method also led to two important observations. Firstly, the traditional RMS solution that heavily employs seat inventory control methods tends to grow out of proportion when a large-scale simulation is involved. Secondly, since time variance is one of the thrust for studying the evolving CATS, a dynamic pricing model that learns to determine optimal prices over time may be a more suitable option.

Table 4 summarizes the capabilities and limitations of the three supply-centric models reviewed.

2.3 Literature Review Summary

Through the literature review, four key findings have been identified.

Finding 1. Models do not capture interactions between consumers and service providers

The volume of air travel demand is typically derived from and driven by the fundamental mobility needs of the general public. However, as it is with most other products and services, this demand profile is influenced by supply-side attributes (contributed specifically by air service providers) such as air fares, flight itineraries, flight duration, and other intangible factors such as service providers' customer satisfaction and reputation. Simultaneously, decisions and actions regarding these attributes are governed by the air travel demand volume and profile over time. These interactions should be investigated for the study of the evolving CATS, treating consumers and service providers as tightly-coupled entities.

MCATS and Jet:Wise assumed a fixed demand function (either known or generated) when analyzing the business case for the service providers. Real world airlines typically make the same assumption based on the immense amount of demand data collected over the many years of operation. However, from an academic research point of view, one of the limitations of using fixed demand functions is that the induced demand due to changes in air fares, routes, and introduction of new concepts cannot be evaluated. ACES faces the same limitation since flight demand data required for simulations are provided either by historical ETMS data or by other demand forecast models.

In a slightly different perspective, but significant nonetheless, transportation activities that are generated at the aggregated level without refinement at the microscopic agent level cannot reflect the emerging behavioral interactions amongst transportation stakeholders. Agent-based models such as *Mi* and Jet:Wise are promising tools for representing these interactions, as signified by the demonstrations of emergent behaviors in transportation activities. However, service provider agents in *Mi* and consumer agents in Jet:Wise are treated only as reactive agents with little sentience to adapt to the changing environment. In summary, service providers should be treated as sentient, goal-seeking stakeholders rather than as mere aircraft operators with simplistic business policies that return fare and time information. Also, consumer agents should be generated with refinement at the microscopic level to properly capture the overall emerging behavioral aspects of consumers' travel patterns in response to the service providers' actions.

Finding 2. Some models focus only on the NAS, but not the NTS

In a realistic transportation environment, air transportation is part of the multimodal travel activities that include ground and maritime transportation. While it is a commonly accepted practice to discard maritime transportation activities, the multimodal/intermodal relationship with the ground transportation system plays a crucial role in shaping aviation demand. Ground transportation acts as a reinforcing and more so as a competing sector to air transportation. The significance of the relationships between these stakeholders gives rise to the consensus that the scope of air transportation system research must be extended beyond the NAS level into the NTS level.

TSAM and Mi address transportation activities at the NTS level. However, ACES, Jet:Wise, and MCATS are developed to investigate the NAS operations in isolation from the rest of the NTS since only the NAS stakeholders are modeled. AvDemand is also developed to generate flight demand sets within the confinement of the NAS scope. The impact of the multimodal/intermodal relationships may be negligible for

ACES since its primary objective is to replicate the functionality of the NAS operations for a given demand set and scenario. However, these relationships contribute significantly to the analysis of air service providers' decision-making and actions under a competitive environment. This competitive environment model loses a significant amount of fidelity when flight demand is treated as a fixed input that is not influenced by the NTS transportation activities as it should be.

Finding 3. Models carry different levels of geographic granularity and validity

Obvious tradeoffs exist between the levels of geographic granularity and computational resources. These tradeoffs are further governed by the modeling objectives and data availability. The designer must consistently uphold the modeling objectives when attempting to locate a balance between these two attributes, while ensuring that there are ample data at the desired level of the granularity for model calibration and validation.

The simulation of transportation activities is derived either from an airport location or a population location within each models' environment. Supply-centric models such as AvDemand, ACES, and MCATS derive transportation activities by modeling hundreds of airport locations. This level of granularity enables focused studies on specific regions within the CONUS, particularly for MCATS in the analysis of regional air service provider concepts. Fortunately, there are ample aviation data for all these airports to facilitate model calibration and validation.

On the other hand, TSAM, *Mi*, and Jet:Wise derive transportation activities from populated residential locations. TSAM and *Mi* use the 1995 ATS database, which is the most conclusive database to date, to calibrate and validate the models. However, as discussed in Appendix A.7, several forms of data anomalies are present in the database, which calls for careful consideration when using and adapting this database for the modeling process. TSAM uses a collection of 3091 counties to represent the CONUS, but the county level output from the model cannot be directly matched against the 1995 ATS data at the Metropolitan Statistical Area (MSA) level. Instead, both the model output and ATS data are aggregated and matched at the state level. On the other extreme, *Mi* aggregates all MSAs in the CONUS into four abstract locales and is directly calibrated against the aggregated ATS data at the national level. The aggregation of the ATS data reduced the severity of data anomalies by offsetting the magnitude of the anomalies. Meanwhile, Jet:Wise uses a collection of 191 Metropolitan Areas to represent the CONUS and uses historical flight data for validation.

Finding 4. Models operate in a static environment

The connotation of the air transportation system as a *living* SoS implies that the system experiences perturbations that propagate to multiple levels of the system over time in the form of dynamic feedbacks. As transportation stakeholders absorb and adapt to these feedbacks, the evolution of the complex system ignite is instigated. This continuous evolution process makes the modeling of the aviation SoS an increasingly daunting task, yet this dynamic behavior is a key contributor towards the complexity of the problem. Of all the reviewed models, MCATS is the only tool that performs a transient analysis although the model is non-adaptive and it is not known for sure if the dynamic feedbacks are captured. The other models perform either annual-based or a same-day simulations that result in static transportation environments. Hence, in order to study the evolving air transportation system, the model should incorporate dynamic analyses and implement adaptive capabilities.

2.4 Research Questions and Hypotheses

Observations are drawn from the insights gained from holistic literature exploration and general experience. Research Questions are posed based on each of these Observations. A Hypothesis that can be tested with the proposed methodology is then offered for each Research Question based on literature review and research experience. Supplementary Questions related to some Research Question-Hypothesis pairs are also posed, which are questions without hypotheses but are intended to be answered through the outcome as well as the process of the proposed methodology itself.

Based on the previous discussions, the following research questions and hypotheses are attained:

Observation 1. The commercial air transportation system is widely regarded as a complex adaptive system. The economics that governs airline operations is complex because it is dynamically driven by competitive behaviors and human-in-the-loop factors.

Research Question 1. *How can one model the complex behavior of the commercial air transportation network system?*

Hypothesis 1. The complexity and competition in the system, both of which are time-dependent derivatives of the demand-supply interactions, must be addressed.

Research Question 1.1. *What is the modeling approach required for capturing complexity of the system?*

Hypothesis 1.1. A network modeling platform that adopts a bottom-up design framework is required. This approach addresses sentience at the constituent level where complex behaviors are derived.

Research Question 1.2. *How can airlines competition be reflected?*

Hypothesis 1.2. The market dynamics derived from the tightly-coupled interactions between airlines and consumers must be captured in order to reflect airlines competition. This is done via an integrative demand-supply model, which employs various transportation forecasting concepts, probabilistic methods, and learning techniques.

Supplementary Question 1.2a. *How does air service providers competition impact the travel demand and behavior of consumers?*

Supplementary Question 1.2b. *How are the different business policies reflected onto the financial performance of airlines?*

Observation 2. Literature review revealed two opposite approaches and levels of granularity for modeling transportation demand: an abstract 4-node agent-based approach and a county-level Four Step Model approach. An approach that can conceivably retain the best of both models to capture spatially-explicit true origin-destination demand is desired.

Research Question 2.1. *What is the approach for capturing true origin-destination demand?*

Hypothesis 2.1. An agent-based approach that inherits trip distribution and mode selection techniques from the Four Step Model is adopted. This approach captures the behavioral aspects of transportation demand and is aligned with the bottom-up design framework posed by Hypothesis 1.1.

Research Question 2.2. *What is the minimum level of granularity required for modeling the spatially-explicit transportation environment?*

Hypothesis 2.2. The level of granularity at the Metropolitan Statistical Area level is required. Primary airports in these locales are used to represent the airport network system. This level of granularity is aligned with that of the 1995 American Travel Survey[4].

Observation 3. Like any other business entity, airlines have complicated functions that are difficult to be fully modeled. There are no existing models that claim to fully represent the functions of an airline.

Research Question 3. *Which functions are the most critical ones in reflecting the competitive behaviors of airlines?*

Hypothesis 3. The modeling of airline pricing and routing functions sufficiently captures the competitive behaviors or airlines at the industry level. Fleet / frequency selection and scheduling dwell into highly detailed operational activities at the vehicle level which are perceived to be beyond the scope of a nationwide system study.

Observation 4. The validity and veracity of agent-based computational models when used to showcase real world systems is as challenging to obtain as it is debatable.

Research Question 4. *How can the validation and verification effort of the integrative demand-supply model be made more tractable?*

[4]The 1995 American Travel Survey is the primary source of data for constructing and calibrating general transportation demand in the U.S.

Hypothesis 4. The integrative demand-supply model can be decoupled to independently calibrate and validate the demand model and supply model against proxy world data sets. If the decoupled models can be independently calibrated and validated, then the integrative demand-supply model is also validated.

Supplementary Question 4a. *What are the calibration and validation criteria for the transportation demand model?*

Supplementary Question 4b. *What are the calibration and validation criteria for the transportation supply model?*

These research questions and hypotheses guide the solution approaches and the corresponding implementation blueprint for the proposed methodology, as presented in Chapter 3 and 4 respectively.

CHAPTER III

SOLUTION APPROACHES

Stemming from the research questions and the corresponding hypotheses posed for this transportation SoS problem, three top level modeling approaches are identified as the building blocks for the proposed methodology.

1. Modeling complex systems
2. Modeling transportation environment
3. Modeling demand-supply interactions

This proposed methodology is in the form of a simulation model of the U.S. commercial air transportation network and is referred to as the [Trans]portation [Net]work (TransNet) methodology hereafter. The formulation of these three solution approaches and the relevant theories and concepts are discussed in this chapter. Concurrently, descriptions of how each approach is devised towards partially or fully addressing a research question is also provided. In closure, the TransNet model architecture is illustrated, serving as the blueprint for implementing the solution approaches as described in Chapter 4.

3.1 Modeling Complex Systems

Hypothesis 1 was posed with three parts in mind. The first part argued that the two necessary and sufficient ingredients for the complex behavior of the CATS in question are the time-variant complexity and competitive elements of the modeled system; complexity elements referring to the self-organizing adaptiveness of the system constituents and competitive elements referring to the goal-driven actions between system constituents that compete for the same pool of resources. The second part proposed the use of a bottom-up design framework and network modeling platform to capture the complexity element of the CATS (**Hypothesis 1.1**). The third part proceeded to claim that the tight interactions between demand-side and supply-side systems must be addressed to reflect competitive elements of the CATS and proposed an integrative demand-supply model to replicate these interactions (**Hypothesis 1.2**). Two aspects of the complex and competitive elements of the system are first discussed.

3.1.1 Complex Adaptive Systems

As a summary of the various existing literature on this subject, complex systems are systems comprising of many constituting components that interact with each other and with the environment, where they collectively exhibit nonlinear aggregated behaviors that are not observed at the individual component level. Furthermore, there is a tendency for the aggregated behaviors to form hierarchical self-organization also known as *emergence*. Amaral and Ottino (2004) provided a highly informational documentation on the studies of complex systems.

A more specific facet of complex systems was founded at the Sante Fe Institute, dealing with complex systems that can change and learn from experience. This field of study was coined Complex Adaptive Systems (CAS) by John Holland and Murray Gell-Mann among others at the Sante Fe Institute (Kauffman, 1993). Holland (1992) described CAS as "a dynamic network of many agents acting in parallel, constantly acting and reacting to what the other agents are doing. The control of a CAS tends to be highly dispersed and decentralized. If there is to be any coherent behavior in the system, it has to arise from competition and cooperation among the agents themselves. The overall behavior of the system is the result of a huge number of decisions made every moment by many individual agents" (Waldrop, 1992).

Based on the short but concise description of CAS above, it is apparent that the U.S. commercial air transportation system (CATS) exhibits many of the defining characteristics of a CAS particularly in generating complex behavior and market dynamics as the underlying driving forces of the system. Recognizing the importance of market dynamics and complex behaviors, the proposed methodology adopted a bottom-up design for generating transportation activities. As documented in Appendix B, the Agent-Based Modeling and Simulation (ABM/S) technique is well-suited for modeling such nonlinear systems that demonstrate emerging complex behaviors. Thus, the TransNet methodology employs the Multi-Agent System (MAS) concept where two classes of agents, namely, consumer agents and service provider agents are conceived. These consumer agents and service provider agents represent the demand-side and supply-side components of the aviation system based on the system-of-systems abstraction depicted in Figure 1. Emerging behaviors involving travel patterns, transportation network configuration, and air carriers competition could then be observed from the interactions between these two classes of agents at the aggregated level.

The adoption of the ABM/S technique and network model for modeling complex systems is geared towards developing a quantitative method for investigating the behavior of the CATS as posed by **Hypothesis 1.1**.

3.1.2 Sentience

The definition for sentience is the condition or quality of being conscious and aware. An agent is deemed sentient if it has deliberative responses towards changes in the environment caused by the actions of other agents within the population. In a Multi-Agent System, the representation of sentience becomes more complicated as both agent-environment interactions and agent-agent interactions become contributing factors to the changing environment. In some circumstances, agent-agent interactions may also directly trigger internal structural changes to the relevant agents.

Here, the concept of deliberative agent behavior (See Appendix B) is invoked, where consumer agents are continuously created and destroyed after every simulation time tick while service provider agents are created at tick zero and are retained throughout the entire simulation. The destruction of consumer agents reduced the computation memory allocation resources without deteriorating the model in any way since consumer agents have no unique sentience that is required for future simulation runs. On the other hand, service provider agents possessed unique sentience that helps them evolve and improve their business models over time. In the construct of these service provider agents, the pricing subagent utilized the dynamic pricing method to improve fare determination for trip requests. This method employed an experiential learning method that is derived from the underlying concepts of the Reinforcement Learning (RL) technique. As a brief introduction, the goal of an RL agent is to maximize the total rewards received upon making a set of actions. A policy function will prescribe to the RL agent on which action to pursuit to achieve this goal. The agent may prefer actions that it has attempted in the past and known to be effective actions, that is, exploitation of past knowledge. However, the agent has to try previously unattempted actions in order to find these new effective actions, that is, exploration of actions. Exploitation and exploration have to be jointly pursued to achieve the task. Thus, the RL agent adopts both strategies and learns to progressively favor and select the best actions (Sutton and Barto, 1998). When these agents update their information banks to reflect the success or failure of each transaction, they instill awareness towards changes in the environment which allows for making better business decisions/actions in the future.

While consumer agents do not keep detailed records of past trips except for the time and cost spent, consumer agents too can instill awareness towards changes in the environment by adjusting their travel patterns using the time and cost budget space concept proposed by Lewe (2005). These travel pattern adjustments include not only mode selections (largely due to airline pricing strategies), but also trip frequencies and distributions (due to pricing and routing strategies as well as macroscopic changes to the transportation network). The use of the previously discussed modeling approaches and techniques, primarily ABM/S, multinomial logit model, and learning methods to construct the integrative demand-supply model under a time-variant environment, will concurrently capture the sentience of both transportation consumers and service providers.

This approach for modeling sentience is intended to address the issues of complex network behavior and airline competition as posed by **Hypothesis 1** in general.

3.2 Modeling Transportation Environment

The transportation environment serves as the platform where the hypotheses posed in the previous chapter can be investigated and the decoupled calibration proposition made in **Hypothesis 4** can be testified. Two necessary characteristics are identified for the transportation environment of the TransNet methodology from the literature reviews of existing air transportation demand research. The solution approaches for developing a spatially-explicit and time-variant environment is provided as follows.

3.2.1 Spatially-Explicit Environment

Literature review of the air transportation demand-side components revealed that existing models employed different levels of granularity for modeling transportation environments depending on the scope and goals of the research. Thus, using the TSAM and *Mi* models as the cornerstones, there is no one correct answer as to which level of granularity is the best. However, based on the capabilities and limitations of the demand-centric models tabulated in Table 3, the goal is to reap the best of both world; capitalizing on providing a spatially-explicit representation of the CONUS while considering intermodal and multimodal relationships as well as the behavioral aspects of consumer travel. Model granularity at the state level is too coarse to accurately reflect true origin-destination demand while model granularity at the county or zip code levels are too refined to extract the aggregated emerging behaviors of transportation activities. This led to the formulation of **Hypothesis 2.2** as discussed below.

The spatially-explicit transportation environment model would require a declaration of geographically-specific location entities, referred to as *locales* hereafter. This locale definition is characterized by the level of geographic granularity and the scope of the problem. For reasons related to calibration and computational resources, the Metropolitan Statistical Area (MSA) level is chosen as the level of granularity for TransNet, similar to that of the 1995 American Travel Survey. This level of granularity is extended to include non-MSA locales grouped at the state level. Meanwhile, the CONUS scope is selected as the geographic boundary of TransNet. Subsequently, the CONUS representation within TransNet is constituted by a collection of 156 MSA locales and 48 non-MSA locales. These 204 locales are computationally represented as coordinate-specific nodes in a spatially-explicit TransNet model, where consumer agents are statistically populated into these locales using the Census demographic data.

All the airports within the U.S. can be classified via the FAA National Plan of Integrated Airport System (NPIAS) airport type categorization. The first classification distinguishes between primary and non-primary airports based on the Annual Passenger Boardings (APB). Primary airports have APB of greater than 10,000 and non-primary airports have APB of less than ten thousand. To name a few, this categorization includes large, medium, and small hub[1] primary[2] airport types as well as non-primary airport types. The composition of all airport types in the Federal Aviation Administration (2005) NPIAS in year 2002 is shown in Table 5. Only primary airports in the CONUS are used to construct the CONUS airport network model. Through a routing subagent analysis, feasible and viable edges linking these airport nodes representing market pairs are created by a route generation algorithm. These nodes and edges are the constituting elements of the network modeling concept, which allow for the investigation of emerging behaviors in the transportation network model.

3.2.2 Time-Variant Environment

Epstein and Axtell (1996) pointed out that "by the large, social science, especially game theory and general equilibrium theory, has been preoccupied with static equilibria, and has essentially ignored time dynamics." Inevitably, the evolving air transportation system can only be aptly analyzed under a time-variant model environment.

[1]Categories of hub are defined by the values in the parentheses in the table, which are the amount of Annual Passenger Boardings (APB) either as a percent or number of APB of the total APB in the U.S.

[2]Primary airports have APB >10,000

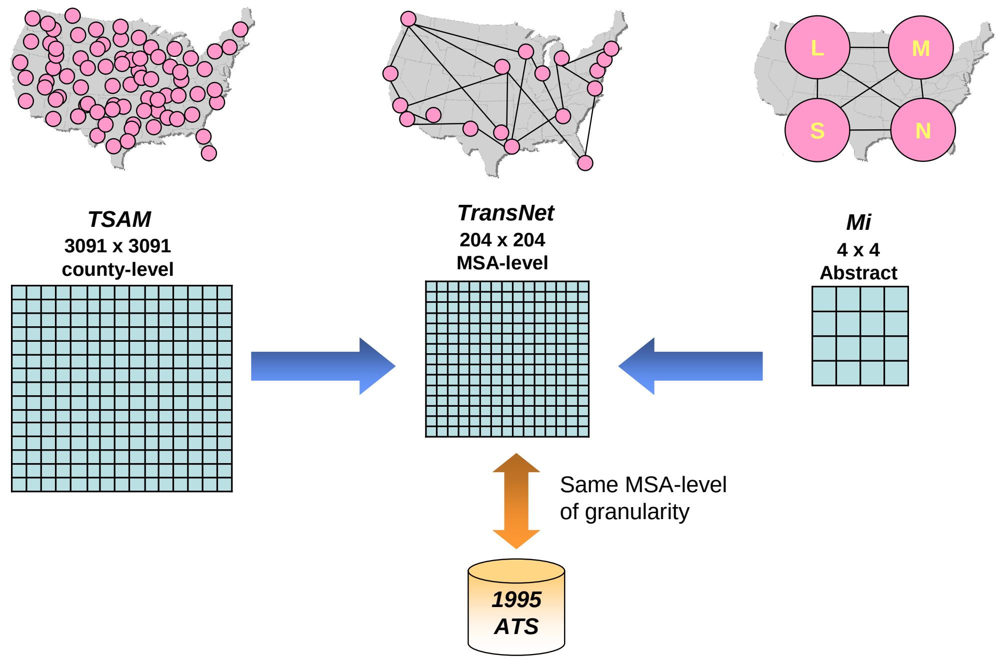


Figure 5: Level of Granularity

Table 5: 2002 FAA NPIAS Airport Types Composition

Number of Airports	Airport Types	Percentage Enplanement
31	Large Hub Primary (>1%)	69.4
37	Medium Hub Primary (0.25%-1%)	19.7
68	Small Hub Primary (0.05%-0.25%)	7.6
247	Non Hub Primary (10k-0.05%)	3.1
127	Non-Primary Commercial Service (<10k)	0.1
278	Relievers	0.0
2,556	General Aviation	0.0

Thus, this solution approach implemented a transient analysis of the aforementioned bottom-up design framework with an embedded integrative demand-supply algorithm by updating key system level variables with records from previous runs; guiding the evolution of TransNet over the simulation time span. A pre-simulation training period is incurred where the *learning* service provider agents are trained to approximate the general characteristics of service providers for multiple time ticks within that period. These characteristics are defined by key airline industry metrics, which may include but not limited to ASM, RPM, average load factors, and market shares. An agent-based simulator tool is used to facilitate the transient analysis over the pre-simulation training period as well as throughout entire the simulation duration. This transient analysis is intended to reveal the evolutionary competition and the true market dynamics within the aviation marketplace.

The overall solution approach for modeling the TransNet transportation environment is depicted in Figure 6.

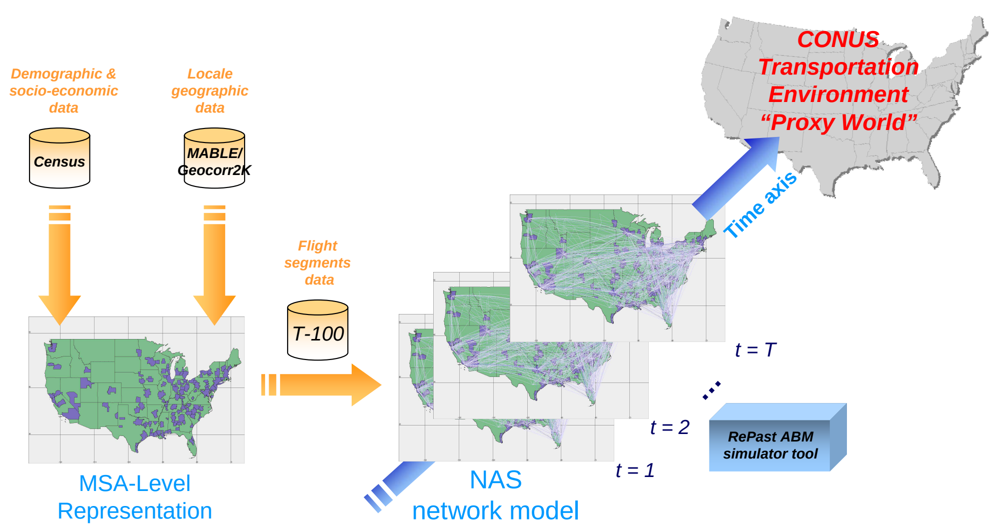


Figure 6: Solution Approach for Modeling Transportation Environment

3.3 Modeling Demand-Supply Interactions

From a microscopic perspective, a consumer interacts with a service provider in the form of a bilateral exchange between transportation service and an agreed sum of monetary currency. These two stakeholders then employ the transportation resource (aircraft, airport, and airspace) under the governance of the FAA to complete the transaction. As these seemingly simple interactions are aggregated, a new interrelationship that is complex, adaptive, and dynamic is developed. This interrelationship generates the intricate momentum that drives the natural market reaction of balancing travel demand and supply, referred to as market dynamics hereafter (Taylor, 1996). In the prevalence of technology innovations, new operating concepts, economic/demographic growths as well as other uncontrollable factors, it is the market dynamics that encapsulate all other factors and ultimately drive the evolution of the air transportation system. Hence, studying market dynamics in a time variant environment is crucial within the context of the aviation SoS research.

Classical economics suggest that in a perfectly competitive market, these interactions act to determine the price and the corresponding quantity bought and sold such that equilibrium is attained (Deardoff, 2006; Renner). Clearly, the aviation marketplace does not operate under perfect competition. As a matter of fact, airline pricing is the definitive example of discriminative pricing in an oligopolistic market, where aircraft seats are sold at multiple price levels depending on certain purchase attributes. However, this does not imply that the market dynamics in the aviation marketplace are unimportant. Rather, market dynamics in the context of the air transportation system are stepping into the domain of evolutionary economics, a modern branch of economics that stresses on complex interdependencies, competition, growth, and resource constraints. While the transportation demand and supply component models do not directly invoke the theories of evolutionary economics, the resulting integrative demand-supply model is capable of showcasing the evolution of the NAS as driven by market dynamics.

3.3.1 Transportation Demand

Hypothesis 1.2 postulated a solution approach for modeling transportation demand that is formulated from the foundations of the agent-based demand model while adopting modeling concepts from the Four Step Model. The agent-based demand model provides the mechanism from which transportation demand can be modeled as an aggregated outcome of microscopic demand in cohesion with the bottom-up approach for modeling complex systems. The demand model inherits much of the theoretical concepts of the *Mi* model, largely due to the commonality of utilizing a bottom-up design framework and that the *Mi* model was successfully calibrated against the 1995 ATS data. In this approach, transportation consumers are represented as agents that are uniquely defined by prescribed geographic, demographic, and socio-economic properties of each locale (See Section 2.1.2.2). Trips are generated and the final trip frequency are determined from the mobility budget space concept. Trip distribution and mode selection are implemented using a gravity-based model and a utility-based logit choice model, both of which are commonly used techniques in the Four Step Model (See Section 2.1.2.1). Detailed implementation steps are provided in Section 4.3.1.

3.3.2 Transportation Supply

The supply model comprises of the NAS infrastructure model and the air service provider model. The NAS infrastructure model is constituted by airports that are located within the 204 pre-selected locales. Since the methodology focuses primarily on the demand-supply integration and the resulting dynamics at the aggregated level, the mechanical assignment of the trips is not modeled. The NAS capacity levels are treated as a constraint function specified by the T-100 segment data and the FAA Airport Capacity Benchmark while delay is assumed as user-determined probability density functions. Meanwhile, the air service provider model utilizes the infrastructure model to construct air service networks that cater to the air transportation demand generated.

3.3.2.1 Air Service Providers

While the NAS infrastructure serves as the physical platform for servicing air transportation demand, airlines or air service providers are the commercial entities that provide the means for servicing the demand within this physical platform; the primary supply-side constituent of the CATS. Throughout its history, the U.S. CATS has evolved dramatically due to changes in the economic landscape of the airline industry, particularly in terms of the business models and operational paradigms of these airlines.

Airlines business models

The Deregulation Act in 1978 triggered the drastic evolution in the airline industry throughout the past three decades. Berardino (1998) attributed this evolution to a hypercompetitive marketplace, that is, when “there are no fundamental strategies or economic advantages that carriers can sustain for any length of time. Over the years, this market condition had resulted in increasing congestion and delays and extreme hike in full fares, causing a widening fare range (Kahn, 2002). Subsequently, two successful business models have emerged, namely, network carriers and niche carriers. Network carriers make use of the fundamental hub economics to gain market share, allowing them to emerge as some of the largest carriers in the nation in terms of network capacity and markets served. This description resonates with aforementioned Big Six legacy carriers, which collectively become the main focal point in this research. On the other hand, niche carriers focus on strategies other than economies of scale to gain market share. These niche markets include but are not limited to low cost carriers (Southwest Airlines and JetBlue), luxury carriers (Virgin Atlantic and Hooters Air), high speed carriers (Concorde), and on-demand carriers (NetJets and Pogo Jets). The low cost carriers are also emphasized since together with the legacy carriers, low cost carriers make up the majority of the commercial air transportation services. Furthermore, these two business models are characterized by the network architecture employed, which remains to be one of the primary interests in transportation research. The on-demand carriers are also discussed since they are becoming notable challengers in the traditional airline industry, particularly for serving business travelers. The number of companies operating business aircrafts in have almost doubled since 1995 and the fractional jet ownership market has grown 62 percent since 2000 (Loyalka, 2005).

Transportation systems are commonly modeled using networks, where nodes represent specific locations and links represent the path or routes connecting different locations. A comprehensive summary of transportation network models is provided in Appendix C to facilitate a better understanding of the following discussion. Transportation networks can be classified in specific categories depending on a set of topological attributes that describe them. Rodrigue et al. (2006) established a basic typology of transportation networks based on criteria such as its geographical setting, the modal choice, the structural characteristics, as well as the point of interest of the network itself; a graphical representation of possible criteria that indicate the classifications of transportation networks are provided by the Rodrigue.

A familiar air transportation network example is the hub-and-spokes versus the point-to-point system. Classifications that are relevant to this example are the network pattern (hub-and-spokes network demonstrates a centralized and strongly centripetal pattern), orientation and extent (point-to-point network limits its orientation and extent to highly demanded city-pairs trips), and dynamic change (deregulation of airlines in the 1970s contributed to the emergence of the hub-and-spokes network). An in-depth discussion of these network elements is provided by Black (2003).

Network carriers operate one or more hub airports and direct passenger flows to and from these hubs. This is known as the hub-and-spokes transportation network, which holds two key economic advantages. Firstly, hub operations allow network carriers to assert dominance over the local traffic by building up service levels within the hub. This dominance results in higher load factors and frequencies at the hub, which then allows network carriers to exploit the pricing either by charging a premium for a non-competitive route or by offering discounts at levels that other carriers have difficulty competing. The second advantage revolves around the economies of scale, where the unit costs of a hub operation is less than a point-to-point operation. This is because the network carrier can operate larger aircrafts and use its ground personnel more efficiently without deteriorating the service levels (Berardino, 1998). These advantages are graphically depicted in Figure 7.

As the name suggests, *low cost carriers* aim at providing air services at a low cost by eliminating many traditional passenger services. To achieve this while ensuring three minimum requirements: safe, on-time, and clean, these carriers typically operate at a much smaller scale and coverage as compared to network carriers. Low cost carriers focus on high volume markets, which leads to the formation of point-to-point transportation networks between these city pairs.

The first successful low cost carriers in the U.S. was Pacific Southwest Airlines (1946), although Southwest Airlines (1971) has been the household name for this niche

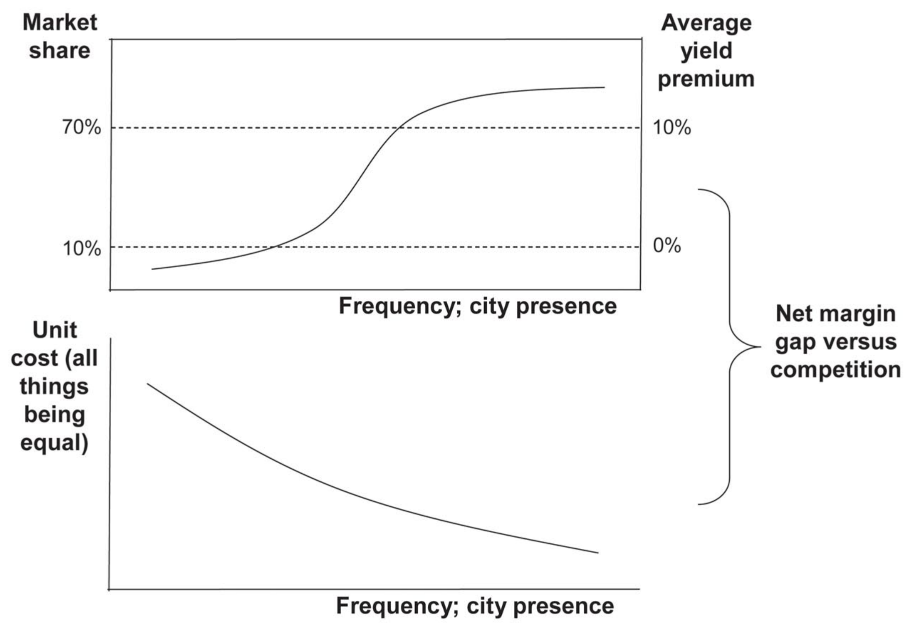


Figure 7: Advantages of Hub Operations [Source: Bernardino (1998, p. 106)]

market. Despite the aforementioned advantages of hub operations, low cost carriers have emerged as the best performers in the market for the past few years. One of the suggested reasons for this is that the effectiveness of hub operations is dampened by the increase in flight frequencies as the low cost carriers gain momentum in these point-to-point markets where excess demand exists. In addition, low cost carriers' emphasis on lowering operating costs alleviate the severity of economic uncertainties in this industry as compared to the incumbent legacy carriers. These carriers kept their operating costs low by maintaining low wages, airport fees (by targeting high demand yet low airport fee markets), and maintenance costs (by having homogeneous fleets).

As the CATS continues to evolve with the increasing pace of life of the modern society, a new niche market focusing on providing *on-demand air services* began to emerge. The main operational difference between an on-demand carrier and a common carrier is that the entire aircraft is rented out versus individual aircraft seats. Doing so allows for much more flexibility in scheduling flights in terms of departure time and destinations.

Investigation of the different business models provide insights into the conceptualization and characterization of the service provider agents in the TransNet methodology. Subsequently, legacy carriers and non-legacy carriers are selected are selected as the two categories for representing service provider agents for three reasons. First, the comparison between legacy and low cost carriers is the most sought after study as far as the modern airline industry is concerned. Second, this categorization provide a mutually exclusive and collectively exhaustive representation of air service providers. Third, legacy carriers have always been composed by the same six flagship carriers: American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, United Airlines, and US Airways, and this provides an uncontested consistency for the time-variant simulation studies and analyses.

Airlines operations

In reality, an air service provider organization is a highly intertwined and complicated assembly of business units, each performing unique functions and possesses unique goals and constraints. Literature review identified the four core functions on these air service providers as i)routing, ii)fleet/frequency selection, iii)pricing, and iv)revenue management. Modeling a full-scale air service provider business model is a daunting task that is perhaps beyond the capability of any one individual. Thus, **Hypothesis 3** postulates that the service provider agent can reflect air service provider's business model by focusing on two core functions, namely, pricing and routing while partially addressing the revenue management function via a dynamic pricing method. A sub-agent concept is developed and adopted to maintain cohesive operability between each core function, where subagents are internal entities of an agent that possess individual goals and constraints while remaining affixed towards the top level goals of the agent.

The pricing function for the service provider agent model is derived from a cost-based analysis, where direct and indirect cost components per seat are computed based on the aircraft class used for the given flight segment. The cost-based method is advantageous over the regression and data-lookup methods because it enables direct control of the different cost components. This allows for simulation studies under different economic scenarios, exorbitant increase in fuel price being one of them [3]. However, one of the challenges of using a cost-based method is the difficulty of obtaining accurate cost components especially if a large number of aircraft types is used. Several measures can be taken to overcome this challenge. First, the number of distinct aircraft types used can be reduced by classifying aircraft types into classes based on general aircraft specifications such as seat capacity and takeoff gross weight. With a more manageable list of aircraft classes and some aggregation at the aircraft type level, the cost components for all reporting air service providers can be extracted from the BTS Form 41 Financial reports. Subsequently, the appropriate fare levels can be determined from Cost Estimating Relationships that are built from these cost components.

Apart from determining the fare levels, the pricing subagent utilized a dynamic pricing method, which differs from the traditional RMS in the sense that the flight fare is not known to the service provider at the trip request arrival; oftentimes the case in reality. The dynamic pricing method is aimed at adjusting the final fare offer by considering the most important pricing factors used by airlines: the advance purchase

[3] During this research, global crude petroleum price rose from USD 25 per barrel in 2003 to over USD 100 per barrel in 2008.

period. By adopting an experiential learning method that shares similar underlying concepts with the Reinforcement Learning method, the awareness or *sentience* in the service provider agents to adjust pricing based on the advance purchase period of the consumers is captured.

Undoubtedly, fleet/frequency selection remains to be an important function. However, this function dwells into highly detailed operational activities at the vehicle level which are perceived to be beyond the scope of this system level study. Therefore, instead of modeling this function explicitly, the fleet and frequency information is captured by using historical airline operations data from the T-100 database for constructing the airline service networks. These airline service networks serve as the baseline network model for service provider agents to carry out the routing function.

The routing subagent for the service provider agent model performs the routing function via a stochastic algorithm that generate route options from the aforementioned baseline network model. To reflect the existing hub-and-spoke system, the first step in the algorithm is to identify airports that serve as hubs for each service provider particularly the network carriers. Hypothetical route options are then probabilistically generated from combinations of connecting flight segments, with the probability of success determined based on the flight frequencies of all constituting flight segments as well as the overall trajectory of the route option. The general consensus is that there is a higher probability of constructing a route option when there are larger number of flights between the airports involved and when the flight distance traversed is shorter. Evidently, the shortest distance possible is a non-stop route option and all other connecting route options are deemed inferior. When considering ONLY the trajectory distance of the route options, shortest path algorithm such as the Dijkstra's algorithm may be used. In addition to this algorithm, a network adaptation algorithm allows the service network to evolve based on the market-driven air travel demand changes over time.

3.3.3 Integrative Demand-Supply Model

Many aviation researches in the past have treated air transportation demand and supply as fully independent components with more emphasis on the latter, particularly because issues involving airspace and airport capacity remain the primary cause of concern for key players in both industrial and governmental institutions. The TransNet demand and supply component models too, retained independence and modularity in that each component model can be independently executed as long as a meta-model of the other component model is provided. However, the transportation activities simulation in the methodology is conceptualized by concurrently addressing the highly coupled interactions between these two component models in replication of what one would expect from a real traveler-airline transaction. Interestingly enough, a subsequence of the present day hub-and-spokes system is such that air transportation demand is realized from the true origin (L_1) to the intended destination (L_3) while air transportation supply, more commonly known as *enplanements*, is realized at the segment level from the origin airport to the destination airport ($L_1 \rightarrow L_2$ and $L_2 \rightarrow L_3$)as illustrated in Figure 8. This disparity further complicates the demand-supply interactions, at least in the interest of air service providers since understanding true O-D demand enables better prediction and management of the seat inventory levels.

Based on all the solution approaches presented, the top level solution approach for modeling the demand-supply interactions in the TransNet methodology is depicted in Figure 9 and a detailed blueprint of the integrative demand-supply algorithm is discussed in Section 4.3.3.

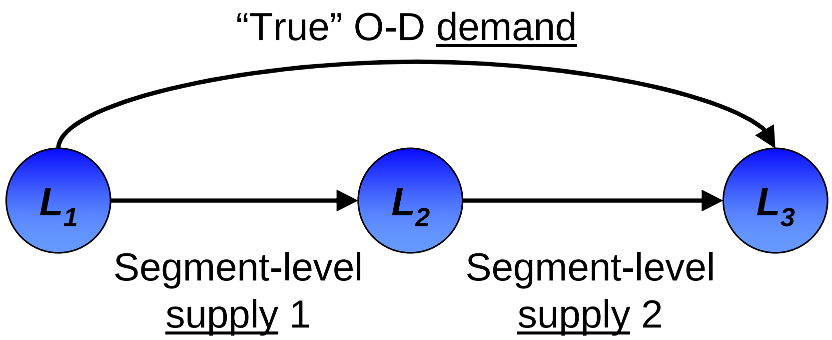


Figure 8: Aviation Demand and Supply Within a Hub-and-Spokes System

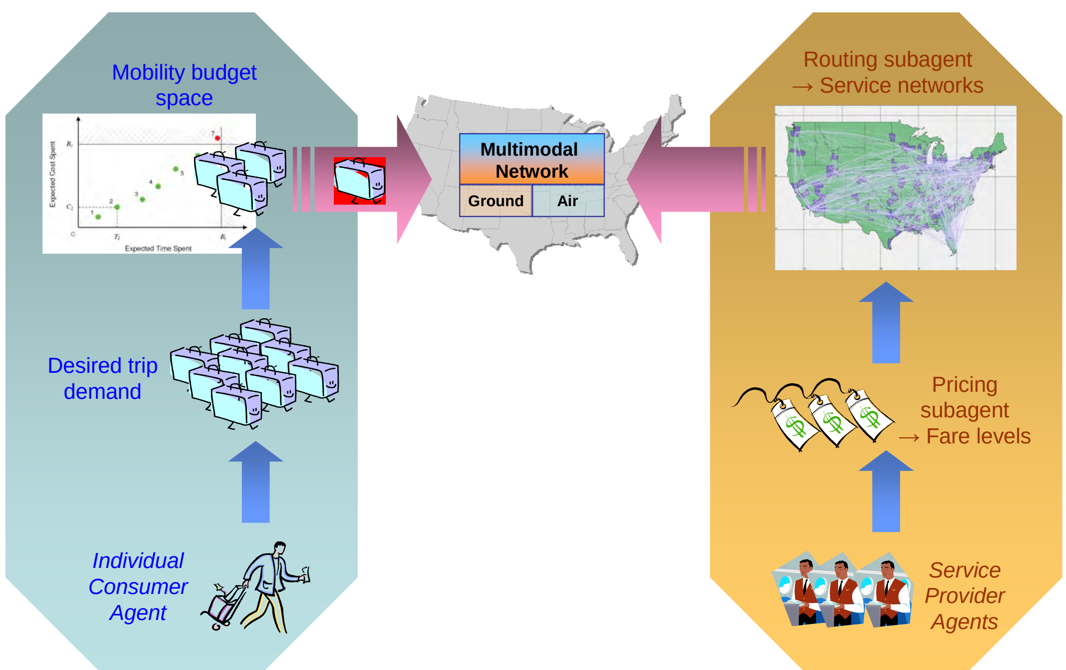


Figure 9: Solution Approach for Modeling Demand-Supply Interactions

With the primary motive of integration being the need to address the transportation demand-supply interactions, the competitive behaviors anticipated from these interactions is intended to facilitate the understanding of airlines competition as posed in **Hypothesis 1.2**.

3.4 Model Architecture

3.4.1 Model Verification and Validation

A model architecture for implementing the TransNet methodology is conceived as a product of the three carefully identified and thoroughly investigated building blocks of the TransNet methodology. These building blocks are revisited below:

Modeling complex systems The ABM/S and experiential learning methods are prescribed as the underlying methods for modeling the U.S. CATS as a complex adaptive system.

Modeling transportation environment A spatially-explicit model of the CONUS in a time-variant environment is prescribed for modeling the transportation environment.

Modeling demand-supply interactions Hypothetical consumer and service provider agents that interacts within the CONUS transportation environment are formulated. The resulting demand-supply interactions generate market dynamics that drive the competitive clockwork for the U.S. CATS.

While the conceptualization of the demand and supply components are concurrently formulated in the form of the integrative demand-supply algorithm, each of the component models is designed to be implemented and executed independently from one another. One of the primary reasons for this is to decouple the complexity of the integrative algorithm and the overall model. Knowing that there could potentially be so many predictor variables for modeling transportation activities, the truly significant governing relationships for each component could be masked by an overly intertwined interrelationships between variables from each components. Having said that, the last piece of the puzzle for fully describing the model architecture pertains to the conformity of the demand-side and supply-side components under the proposed methodology, as posed by **Hypothesis 4**.

Since aviation demand is the primary emphasis of this air transportation research, the lynchpin between the demand model and the supply model is then the true aviation origin-destination demand, $t_{ij,av}$. Aviation enplanement, which is the more typically used and readily available data in aviation research is not directly used because the transportation demand model as was discussed in the previous section, is designed to capture *true O-D demand* instead of the segment-based enplanement tracked by airlines. While it is highly influential towards air service providers' operation strategies, true O-D demand is not yet a well-surveyed area and there are few reliable data sources describing it. This is mainly because true O-D demand is not explicitly documented by mandated aviation reports with the exception of the Airline Origin and Destination Survey (DB1B). Yang et al. (2008) reported significant unsystematic errors in the DB1B database upon closer scrutiny. However, he was able to perform pre-processing treatment on the database to retrieve meaningful true passenger O-D demand. This modified database is coined the Symmetric DB1B (sDB1B) database and is used as the data source for obtaining the benchmark true aviation demand data, $\tau_{ij,av}$. This benchmark data was extracted for the same set of 204 MSA and non-MSA locales defined by the transportation environment model. Since not all of the locales have at least one primary hub airport, the final output of $\tau_{ij,av}$ is a 181 $\times$ 181 matrix instead of a 204 $\times$ 204 matrix. Subsequently, two necessary conditions are hypothesized:

1. The true aviation O-D demand generated by the demand model can be validated against $\tau_{ij,av}$ within an acceptable tolerance.

2. The baseline supply model can capture the majority of $\tau_{ij,av}$ as a demand input within an

acceptable tolerance while remaining comparable in terms of the enplanement traits.

Having satisfied these two conditions, the hypothesis claims that if the decoupled model components are independently validated against the above conditions, then the integrative demand-supply model is also validated.

As a summary of the solution approaches discussed, Figure 6 tabulates how each solution approach was designed to directly map against one or more of the hypotheses posed in Section 2.4.

Table 6: Mapping of Solution Approaches to Hypotheses

Section	For Modeling:	Addresses Hypotheses:
3.1.1	Complex adaptive systems	H1.1
3.1.2	Sentience	H1
3.2.1	Spatially-explicit environment	H2.2
3.2.2	Time-variant environment	H1
3.3.1	Transportation demand	H2.1
3.3.2	Transportation supply	H3
3.3.3	Demand-supply interactions	H1.2
3.4.1	Model verification and validation	H4

3.4.2 Blueprint

The model architecture blueprint for the proposed methodology is illustrated in Figure 10 along with the key sub-components required for satisfying the two primary conditions. The intensive data-dependence for both model construction and calibration & validation purposes, made possible through the database-enabled modeling environment, are also depicted in the model architecture.

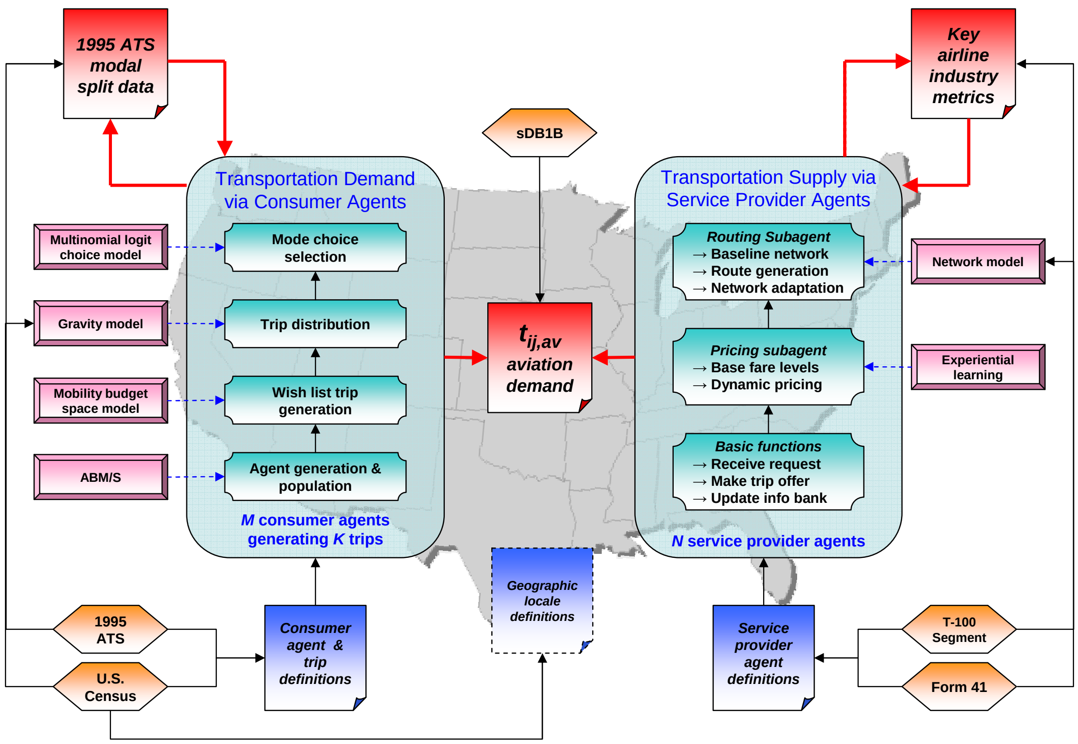


Figure 10: Model Architecture of Integrative Demand-Supply Framework

CHAPTER IV

IMPLEMENTATION

The proposed TransNet methodology is a large scale simulation model of the U.S. CATS via adaptive consumer agents and service provider agents. At the heart of this methodology is the *integrative demand-supply model*, which provides the underlying entities and methods for simulating transportation activities via two independent but integrative model components: a transportation demand model and a transportation supply model.

Successful implementation of this integrative demand-supply model requires a well-designed model architecture. The solution approaches in Chapter 3 served as the foundation for formulating this model architecture. A modeling and simulation framework is first developed, emphasizing three core concepts: object-oriented approach, database-enabled modeling environment, and transient analysis (Section 4.1). Using this framework as the implementation platform, a *transportation environment model* is developed to create a spatially-explicit virtual world where transportation activities simulation can be performed and analyzed (Section 4.2). With these two complementary components in place, the model architecture can be formulated. This model architecture along with the two integrative model components are thoroughly discussed in Section 4.3.

4.1 Modeling & Simulation Framework

Three core concepts were employed in the formulation of the modeling and simulation framework for the TransNet methodology: object-oriented approach, database-enabled environment, and transient analysis. The utilization of each core concept for the specific design requirements of this framework are first discussed. The resulting computational framework is then illustrated as a hierarchical multi-capability framework for modeling large scale simulation systems.

4.1.1 Object-Oriented Modeling Approach

Object-oriented modeling approach

Initially derived from the realm of computer programming, object-oriented modeling approach is a problem-solving cum design approach has been adopted by a wide variety of disciplines and applications ranging from structured finance (Cherubini and Lunga, 2007) to astronomical database design (Brunner et al., 1995) to airport operations modeling (Zhong, 1997). While this approach possesses many key ideas from the outset of programming methods, the general concept revolves around treating a system as a group of independent but interacting objects. Apart from allowing a system to be decomposed into its constituents, object-oriented modeling approach also enables plug-and-play capabilities where additional features and tool sets can be appended to the core building blocks of the model; an encouraging concept towards creating sustainable and adaptive models.

The object-oriented modeling approach is well-suited for formulating the TransNet modeling framework, which is deeply rooted into the bottom-up object-oriented ABM/S framework to begin. Since there are many processes and components in the modeling of transportation activities in the NAS and NTS, four mutually exclusive and collectively exhaustive categories of objects are prescribed. The *agent-related objects* represent consumer agent and service provider agent objects, which make up the two entities that trigger transportation activities. The *trip-related objects* represent trip and service offers objects, which are entities that represent transportation activities. The *locale-related objects* represent locale and airport objects, which create the planar environment for populating agents and executing transportation activities. Lastly, the *flight-related objects* represent flight segment, route options, vehicles, and aircraft objects, which provide the means of executing transportation activities. Descriptions for all objects are tabulated in Table 7 and references to these objects by the object names are used throughout the remaining of this document.

Table 7: Object Definitions in TransNet

Category	**Objects**	**Represents:**
Locale-related	Localeobject	204 MSA and non-MSA locales in the CONUS
	Airportobject	273 airports in the CONUS
Agent-related	Consumeragent	Household and enterprise agents that generate trip demand
	Servprovagent	Service provider agents provide air transport services
Trip-related	Tripobject	Trips demanded by Consumeragents
	Offerobject	Offers made by Servprovagents to execute Tripobjects
Flight-related	Segmentobject	Flight segments that are aggregated on monthly basis
	Routeobject	Collection of Segmentobjects that provide route options
	Vehicleobject	Transportation modes for executing trips
	Aircraftobject	Subset of Vehicleobjects; aircrafts utilized by Servprovagents

4.1.2 Database-Enabled Modeling Environment

One of the main achievements of this research is the spatially explicit and quantitative translation of the highly complex CONUS transportation environment into a 204-locale network model. Besides that, hundreds of thousands of Consumeragents representing traveling consumers are created to generate over three millions trips a year in a simulation exercise that ran over multiple years. The data required in this large-scale multi-disciplinary research are provided in different formats and are obtained from various difference sources. Furthermore, the sheer amount of data transferred before, during, and after each simulation run called for a highly effective and efficient data management system. Subsequently, the modeling platform is designed to have full access to external databases such that data invocation and storage can be conveniently executed. These databases are listed below:

1. Multiyear segment flight data as recorded by the Bureau of Transportation Statistics (BTS) Form 41 Traffic (most commonly known as the T-100) database.

    - Segmentobjects that constitute the baseline network model are constructed by sampling the T-100 database for designated month and year.
    - The characterization of aircraft classes with different cost structure based on seat capacity is conceived by analyzing T-100 segment flight data in conjunction with Form 41 Financial Reporting data.

2. Multiyear carrier financial reportings as recorded by the BTS Form 41 Financial Report.

    - Direct operating cost components and structure are determined from the Schedule P-52 table of this database.
    - Indirect operating cost components and structure are determined from the Schedule P-7 table of this database.

3. A list of all primary and commercial service airports in the United States with information on hub type, enplanements, and location coordinates among others.

    - Airportobjects are constructed from the list of i) primary airports (large, medium, and small hubs) that ii) resides in the 204 locales.

4. Multiyear geographic, demographic, and socioeconomic information as reported by the United States Census database.

    - Metropolitan Statistical Areas (MSA) geographic definitions and location coordinates are determined from this database.

- Demographic (population and household counts among others) properties for all locales are determined from this database.
- Socioeconomic (income distribution and mean earners per household among others) properties for all locales are determined from this database.

5. Travel data for Americans as reported by the 1995 American Travel Survey (ATS).

   - Household and individual trips O-D matrices are derived from this database.
   - Critical distributions and reference tables for constructing the TransNet model are extracted from this database: trip party size, trip frequency, and trip purpose distributions among others.

6. Multiyear flight coupon data collected from five percent of all reporting flights as recorded by the BTS DB1B database.

   - DB1B Coupon data are used to create an aviation demand O-D matrix as an alternative to the O-D matrix extracted from the 1995 ATS.

7. Simulation input data are recorded for tracking and query purposes.

   - List of 204 locales in the CONUS along with locale parameters and information.
   - List of 273 airports utilized in the CONUS with corresponding airport information.
   - List of 4 aircraft classes utilized by service provider agents with corresponding performance and cost parameters.

8. Simulation output data are recorded for tracking and query purposes and for feeding forward into future simulation runs as input parameters.

   - All Consumeragents with updated mobility budget space information.
   - All wishlist Tripobjects generated by consumer agents with trip information.
   - All executed Tripobjects by Consumeragents with trip and mode choice information.
   - All Servprovagents with updated performance and inventory information.

- All Segmentobjects along with updated performance and operations information.
- All Routeobjects with updated performance and operations information.

4.1.3 Transient Analysis Framework

By employing the ABM/S method, transportation activities within the TransNet methodology is simulated at the microscopic level with coercive interactions between Consumeragents and Servprovagents. The resulting Tripobjects are collectively executed to represent a single-day operation at the CONUS-wide transportation environment under normalcy conditions. The U.S. Department of Transportation (1999) reported 1.8 million household trips[1] within the CONUS on an average day in the year 1995, out of which 320,000 trips were carried out via commercial air carriers.

One of the solution approaches for answering the research questions posed is to model a time-variant environment where the transient analysis of the simulation can be performed. This generally means that the simulation will be progressive over a specified number of computational cycles, known as simulation *tick* hereafter, while retaining a dependency on the outcomes of the previous simulation ticks. Most demand models perform this transient analysis by assuming a direct growth factor on the trip demand, whether in a homogeneous or heterogeneous manner. The TransNet methodology generates trip demand based on demographic and socio-economic properties of each locale along with a mobility budget space approach for determining the actual trip frequencies for agents. Since growth factors for demographic and socio-economic properties are more readily available than for growth factors for trip demand directly, the transient analysis in TransNet can be treated homogeneously and with a higher level of confidence. In addition, the change in time value of money is captured by addressing the Consumer Price Index for the given simulation time

[1]Only long distance trips greater than 100 miles were recorded by the ATS.

frame for all relevant monetary metrics.

An agent-based simulator tool called RePast was utilized for modeling the Multi-Agent System in the TransNet methodology (Tatara et al., 2006). There is a built-in *Scheduler* function in RePast that is responsible for performing time-progressive simulation runs for a given number of simulation ticks and is used to facilitate the transient analysis framework. Using the aforementioned representative single-day as the basis for the simulated trip volume, the level of granularity for the simulation tick can be determined by the user depending on the research scope and the corresponding demand and supply input data. For instance, a day-to-day NAS operation simulation may use a simulation tick of one day while a long-term transportation behavioral study may use a simulation tick of one year, as long as the model input data is coherent with the granularity and scope of the intended study.

The scope of the case study for demonstrating the TransNet methodology as discussed in Section 6 emphasized the medium to long term impact of transportation dynamics on the U.S. CATS. Since air carriers' data particularly the Form 41 Financial Reports data are typically recorded on a quarterly basis, the simulation tick for the overall simulation exercise is selected to be one quarter. The choice of a quarterly tick also reduced the computational time significantly due to the high setup cost of recording data when initializing the model and when recording the simulation outcome towards the end of the simulation.

4.2 Transportation Environment Model

The scope of this research encompasses transportation activities that are engaged within the CONUS. Thus, the overall transportation environment for this research is fabricated as a spatially explicit representation of the CONUS at the MSA level (Section 4.2.1). Within this geographical boundary, the NAS is then modeled as a prescribed network of active airports (Section 4.2.2). Finally, the considerations for intermodal and multimodal relationships between the different transportation modes are discussed next (Section 4.2.3).

4.2.1 Spatially Explicit Representation of the CONUS

The solution approaches proposed that the TransNet methodology should adopt a level of granularity that is more intricate than the abstract 4-locale *Mi* model yet not quite as dense as the county level TSAM. For the purposes of combining the best elements of both models while allowing direct calibration against the 1995 ATS, the level of granularity at the MSA level is chosen for TransNet. The 1995 ATS depicted the Continental United States (CONUS) as a collection of 168 MSAs. Under two observed conditions, this collection of MSAs is pre-processed and redefined before being utilized as the core building block of the TransNet transportation environment. The first condition is that there are several MSAs that span across more than one state and thus are reported as locales sharing the same MSA name but in different states. These locales are the Cincinnati MSA (Ohio, Kentucky), Kansas City MSA (Kansas, Missouri), Philadelphia MSA (Pennsylvania, New Jersey), Portland-Vancouver MSA (Oregon, Washington), St. Louis MSA (Missouri, Illinois), and Washington MSA (District of Columbia, Maryland, Virginia). These locales are combined to simplify the geographic modeling of the CONUS as well as to avoid possible confusions when using the Census-defined MSA data for model construction. The MSA locale list is subsequently reduced to 161 locales.

The second condition pertains the county-state boundary definitions in parts of the New England region (Connecticut and Massachusetts) where several counties are individually shared by multiple states in this region. There are two main reason why this condition is significant in the MSA locale definition for TransNet. First, the land area and population count for these MSA locales are relatively small compared to the other MSA locales in the ATS database. Combining smaller locales in the same vicinity reduces the complexity yet does not significantly deteriorate the fidelity of the geographic model. Second, a well-defined county list for each MSA locale is desired such that more accurate demographic and economic profiles may be prescribed had a different level of granularity is chosen in future research. Subsequently, the final collection of MSA locales used for defining the transportation environment is reduced to 158 locales.

Demographic and geographic data for each of the finalized MSA locales are retrieved next in the form of the population count and population centroid. For reasons related to the pre-simulation calibration to be discussed later in Section 5, the year 1990 is chosen as the baseline year for which population count data was extracted from the Census database. The MABLE/Geocorr2k tool created by the Missouri Census Data Center was used to retrieve population centroids for the MSA locales for year 2000. While population density may have changed within each MSA from 1990 to 2000 causing the population centroid to shift, it is assumed that this shift is negligible. Considerations for non-MSA locales are discussed next.

A close scrutiny of the 1995 ATS database showed that the trip demand involving (either originating from or going to) non-MSA locales contribute to nearly 60 percent of the total trips in the CONUS and over 25 percent of trips via air transports as shown in Figure 11]. However, these locales are abstracted at the individual state level when in reality they represent dispersed land areas unoccupied by MSA locales in that state. While this causes a tremendous loss of spatial-explicitness in the environment definition, the travel activities from these locales must not be overlooked.

A pseudo-abstract representation of these non-MSA locales is adopted to remedy

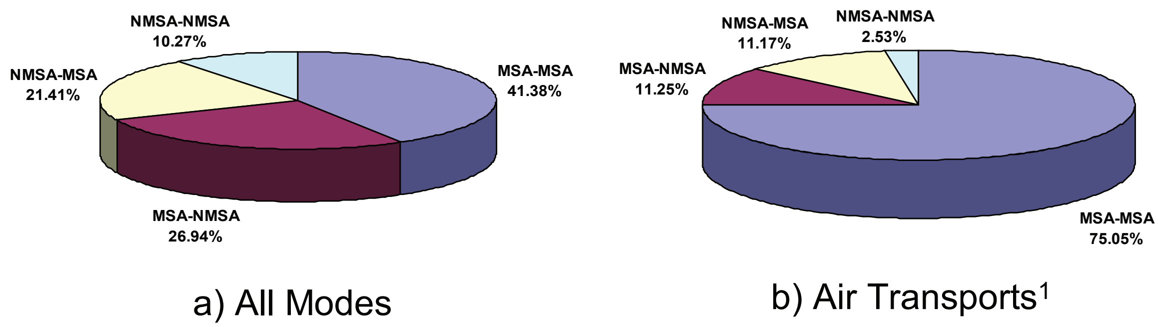


Figure 11: Origin-Destination Categories of the 1995 ATS by Percentage Contribution to Total Trips

1 Air transports include commercial airplane and corporate/personal airplane
Source: 1995 American Travel Survey, U.S. DOT-BTS

this problem. This technique is conceived as a subjective and probabilistic displacement of individual consumer agents within these locales. First, a spatially-explicit representative centroid of the population centroid for the given non-MSA locale must be subjectively identified. Several graphical data sources and tools are used to identify this centroid: an MSA locations map of the United States (U.S. Census Bureau, 2000), a population density map of the United States (U.S. Census Bureau, 2000), a satellite image of the United States at night showing city lights (U.S. National Oceanic and Atmospheric Administration, 2007), and the Google Earth software. Using these tools in conjunction with personal judgments by the designer in sorting out MSA population while observing the overall population density and population concentration in the given state, the approximated population centroid location is identified using the Google Earth software.

To begin populating individual consumer agents in a non-MSA locale, the non-MSA land area is first calculated by subtracting the total land area of MSA locales from the total land area of the given state. This non-MSA land area is further assumed to be generically enclosed within a circle centered at the previously determined representative centroid, from which the radius of this circle, R is calculated from simple geometry given the land area. This circle is a representative of the boundary in which agents can be displaced for the locale. A displacement path determines the origin location for the Consumeragent as a straight line away from the population centroid defined by a displacement radius r and a displacement angle θ, which are uniformly sampled. These two displacement parameters probabilistically determine the exact coordinate location for populating a consumer agent residing in this pseudo-abstract non-MSA locale. With this simple technique, TransNet now captures the spatial-explicitness of non-MSA locales without significantly jeopardizing the model's fidelity and without having to adopt computationally costly methods such as county level detailing. The overview of the probabilistic displacement technique is shown in Figure 12.

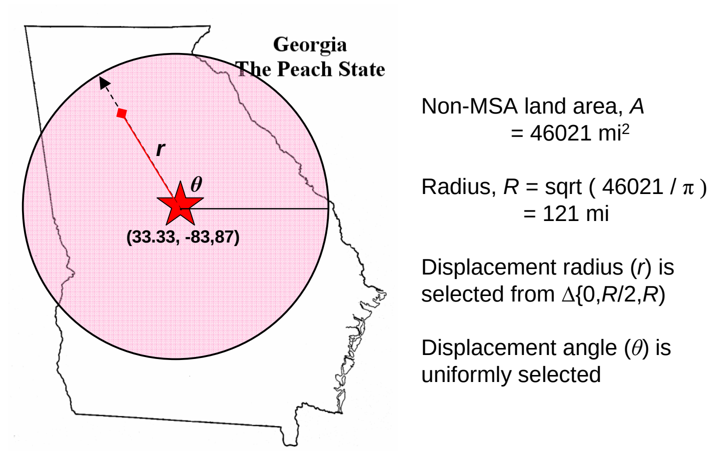


Figure 12: Non-MSA Consumer Agents Probabilistic Displacement Method

Subsequently, the spatially-explicit representation of the CONUS in TransNet is constructed as a collection of 158 MSA locales and 47 non-MSA locales as depicted in Figure 13 as well as Tables 8, 9, and 10.

Table 8: Geographic & Demographic Data Used in TransNet, Base Year = 1990

No	METCODE	METNAME	STPOST	MSAID [1]	POP	LAT	LON	AREA [2]
1	80	Akron, OH PMSA	OH	AKROH	657,575	41.12	-81.46	927
2	160	Albany-Schenectady-Troy, NY MSA	NY	ALBNY	809,642	42.79	-73.85	2,878
3	200	Albuquerque, NM MSA	NM	ALBNM	599,416	35.10	-106.62	9,297
4	240	Allentown-Bethlehem-Easton, PA MSA	PA	ALLPA	686,688	40.67	-75.45	1,476
5	440	Ann Arbor, MI PMSA	MI	ANNMI	282,937	42.18	-83.80	723
6	460	Appleton-Oshkosh-Neenah, WI MSA	WI	APPWI	315,121	44.20	-88.44	1,620
7	520	Atlanta, GA MSA	GA	ATLGA	3,068,975	33.82	-84.35	8,480
8	560	Atlantic-Cape May, NJ PMSA	NJ	ATLNJ	224,327	39.33	-74.64	671
9	600	Augusta, GA MSA	GA	AUGGA	435,799	33.49	-82.00	3,325
10	640	Austin-San Marcos, TX MSA	TX	AUSTX	846,227	30.31	-97.74	4,280
11	680	Bakersfield, CA MSA	CA	BKRCA	544,981	35.37	-118.92	8,161
12	720	Baltimore, MD PMSA	MD	BALMD	2,382,172	39.30	-76.63	3,104
13	760	Baton Rouge, LA MSA	LA	BTRLA	623,850	30.44	-91.05	4,215
14	840	Beaumont-Port Arthur, TX MSA	TX	BEATX	361,218	30.07	-94.04	2,388
15	875	Bergen-Passaic, NJ PMSA	NJ	BERNJ	1,278,554	40.92	-74.11	419
16	960	Binghamton, NY MSA	NY	BGHNY	264,497	42.12	-76.01	1,238
17	1000	Birmingham, AL MSA	AL	BIRAL	956,646	33.52	-86.76	5,370
18	1080	Boise City, ID MSA	ID	BSEID	319,596	43.61	-116.39	1,645
19	1120	Boston-Lowell, MA PMSA	MA	BOSMA	4,133,895	42.24	-71.06	4,511
20	1125	Boulder-Longmont, CO PMSA	CO	BLDCO	225,339	40.05	-105.18	751
21	1280	Buffalo-Niagara Falls, NY MSA	NY	BUFNY	1,189,340	42.93	-78.81	2,367
22	1320	Canton-Massillon, OH MSA	OH	CANOH	394,106	40.82	-81.37	980
23	1440	Charleston-North Charleston, SC MSA	SC	CHANC	506,877	32.92	-80.04	3,163
24	1480	Charleston, WV MSA	WV	CHAWV	307,689	38.38	-81.71	2,547
25	1520	Charlotte-Gastonia, NC MSA	NC	CHLNC	1,024,690	35.24	-80.84	3,147
26	1560	Chattanooga, TN MSA	TN	CHTTN	433,210	35.03	-85.25	2,138
27	1600	Chicago, IL PMSA	IL	CHIIL	6,894,440	41.86	-87.88	5,344
28	1640	Cincinnati OH-KY PMSA	OH	CINOH	1,844,915	39.14	-84.46	4,466
29	1680	Cleveland-Lorain-Elyria, OH PMSA	OH	CLEOH	2,102,248	41.47	-81.65	3,979
30	1720	Colorado Springs, CO MSA	CO	COSCO	409,482	38.87	-104.77	2,689
31	1760	Columbia, SC MSA	SC	COLSC	548,936	34.01	-81.08	3,834
32	1840	Columbus, OH MSA	OH	COLOH	1,405,168	39.99	-82.93	4,014
33	1880	Corpus Christi, TX MSA	TX	CCTTX	367,786	27.78	-97.43	2,401
34	1920	Dallas, TX PMSA	TX	DALTX	2,622,562	32.88	-96.78	5,819
35	2000	Dayton-Springfield, OH MSA	OH	DAYOH	843,835	39.80	-84.12	1,716
36	2020	Daytona Beach, FL MSA	FL	DAYFL	370,737	29.13	-81.13	1,432
37	2080	Denver, CO PMSA	CO	DENCO	1,650,489	39.71	-104.97	8,387
38	2120	Des Moines, IA MSA	IA	DMEIA	416,346	41.60	-93.67	2,912
39	2160	Detroit, MI PMSA	MI	DETMI	4,248,699	42.34	-83.20	4,235
40	2281	Dutchess County, NY PMSA	NY	DCHNY	259,462	41.69	-73.84	825
41	2320	El Paso, TX MSA	TX	ELPTX	591,610	31.78	-106.39	1,015
42	2360	Erie, PA MSA	PA	ERIPA	275,572	42.07	-80.07	1,558
43	2400	Eugene-Springfield, OR MSA	OR	SPROR	282,912	44.04	-123.12	4,722
44	2440	Evansville, IN MSA	IN	EVSIN	324,858	37.97	-87.54	2,348
45	2560	Fayetteville, NC MSA	NC	FYVNC	297,569	35.06	-78.94	1,051
46	2640	Flint, MI PMSA	MI	FLTMI	430,459	43.01	-83.70	649
47	2680	Fort Lauderdale, FL PMSA	FL	FLAFL	1,255,531	26.14	-80.22	1,320
48	2700	Fort Myers-Cape Coral, FL MSA	FL	FMYFL	335,113	26.58	-81.87	1,212
49	2760	Fort Wayne, IN MSA	IN	FWYIN	354,435	41.06	-85.15	1,368
50	2800	Fort Worth-Arlington, TX PMSA	TX	FWATX	1,366,732	32.74	-97.27	3,465
51	2840	Fresno, CA MSA	CA	FRSCA	667,490	36.78	-119.80	6,017
52	2960	Gary, IN PMSA	IN	GRYIN	643,037	41.53	-87.34	2,113
53	3000	Grand Rapids-Muskegon-Holland, MI MSA	MI	GRAMI	992,669	42.96	-85.83	5,981
54	3120	Greensboro–Winston-Salem–High Point, NC MSA	NC	GRBNC	901,478	36.03	-80.00	3,493
55	3160	Greenville-Spartanburg, SC MSA	SC	GRVSC	698,948	34.84	-82.30	2,849
56	3200	Hamilton-Middletown, OH PMSA	OH	HMTOH	289,157	39.41	-84.50	467
57	3240	Harrisburg-Carlisle, PA MSA	PA	HBGPA	474,242	40.29	-76.86	871
58	3280	Hartford, CT MSA	CT	HARCT	1,123,678	41.75	-72.66	1,607
59	3290	Hickory-Morganton, NC MSA	NC	HICNC	292,405	35.77	-81.40	1,666
60	3360	Houston, TX PMSA	TX	HOUTX	3,767,233	29.82	-95.42	10,062
61	3440	Huntsville, AL MSA	AL	HUNAL	293,047	34.76	-86.67	1,420
62	3480	Indianapolis, IN MSA	IN	INDIN	1,294,217	39.82	-86.11	3,888
63	3560	Jackson, MS MSA	MS	JSKMS	446,941	32.33	-90.17	3,795
64	3600	Jacksonville, FL MSA	FL	JSVFL	925,213	30.25	-81.62	3,698
65	3640	Jersey City, NJ PMSA	NJ	JCYNJ	548,267	40.74	-74.06	47
66	3660	Johnson City-Kingsport-Bristol, TN MSA	TN	JHNTN	436,047	36.47	-82.39	2,910
67	3720	Kalamazoo-Battle Creek, MI MSA	MI	KZOMI	429,453	42.27	-85.51	2,388
68	3760	Kansas City, MO-KS MSA	KS	KCYKS	1,636,527	39.04	-94.57	7,949

1 First three characters indicate locale name and last two chracters indicate state name

2 Land area of locales measured in square miles

This table reports 205 locales but the TransNet methodology models only 204 where the Evansville, IN MSA is discarded since no data for this locale is reported by the 1995 ATS

Table 9: Geographic & Demographic Data Used in TransNet, Base Year = 1990 (Continued)

No	METCODE	METNAME	STPOST	MSAID [1]	POP	LAT	LON	AREA [2]
69	3840	Knoxville, TN MSA	TN	KNXTN	534,917	35.93	-83.97	1,932
70	3980	Lakeland-Winter Haven, FL MSA	FL	LKLFL	405,382	28.02	-81.81	2,010
71	4000	Lancaster, PA MSA	PA	LCTPA	422,822	40.07	-76.29	984
72	4040	Lansing-East Lansing, MI MSA	MI	LSGMI	432,684	42.71	-84.56	1,715
73	4120	Las Vegas, NV MSA	NV	LASNV	741,368	36.05	-115.07	8,091
74	4280	Lexington, KY MSA	KY	LEXKY	348,428	37.98	-84.46	1,484
75	4400	Little Rock-North Little Rock, AR MSA	AR	LRKAR	534,943	34.81	-92.32	4,198
76	4480	Los Angeles-Long Beach, CA PMSA	CA	LALCA	8,863,052	34.06	-118.24	4,752
77	4520	Louisville, KY MSA	KY	LOUKY	1,056,156	38.24	-85.72	4,196
78	4680	Macon, GA MSA	GA	MACGA	206,786	32.73	-83.67	1,738
79	4720	Madison, WI MSA	WI	MADWI	432,323	43.07	-89.39	2,802
80	4880	McAllen-Edinburg-Mission, TX MSA	TX	MALTX	383,545	26.23	-98.18	1,583
81	4900	Melbourne-Titusville-Palm Bay, FL MSA	FL	PBYFL	398,978	28.24	-80.69	1,557
82	4920	Memphis, TN MSA	TN	MEMTN	1,067,263	35.13	-89.91	4,700
83	5000	Miami, FL PMSA	FL	MIAFL	1,937,194	25.78	-80.29	2,431
84	5015	Middlesex-Somerset-Hunterdon, NJ PMSA	NJ	MSXNJ	945,584	40.51	-74.44	755
85	5080	Milwaukee-Waukesha, WI PMSA	WI	MILWI	1,432,149	43.08	-88.04	3,322
86	5120	Minneapolis-St. Paul, MN MSA	MN	MPSMN	2,538,776	44.99	-93.25	6,364
87	5160	Mobile, AL MSA	AL	MOBAL	378,643	30.65	-88.06	1,644
88	5170	Modesto, CA MSA	CA	MODCA	370,522	37.62	-120.96	1,515
89	5190	Monmouth-Ocean, NJ PMSA	NJ	MTHNJ	95,089	40.15	-74.17	620
90	5240	Montgomery, AL MSA	AL	MONAL	305,175	32.41	-86.28	2,786
91	5360	Nashville, TN MSA	TN	NSHTN	305,175	36.13	-86.70	5,763
92	5380	Nassau-Suffolk, NY PMSA	NY	NASNY	2,609,212	40.77	-73.35	2,826
93	5480	New Haven-Stamford-Norwalk, CT PMSA	CT	NHVCT	1,631,864	41.36	-72.86	1,699
94	5520	New London-Norwich, CT MSA	CT	NLNCT	254,957	41.44	-72.05	772
95	5560	New Orleans, LA MSA	LA	NORLA	1,264,383	30.02	-90.10	7,097
96	5600	New York, NY PMSA	NY	NYCNY	10,378,627	40.78	-73.91	1,921
97	5640	Newark, NJ PMSA	NJ	NEWNJ	1,959,855	40.79	-74.34	2,257
98	5660	Newburgh, NY PMSA	NY	NBHNY	324,845	41.42	-74.24	1,664
99	5720	Norfolk-Virginia Beach-Newport News, VA MSA	VA	NORVA	1,450,855	36.92	-76.31	3,897
100	5775	Oakland, CA PMSA	CA	OAKCA	2,080,434	37.80	-122.08	1,623
101	5880	Oklahoma City, OK MSA	OK	OKLOK	971,042	35.45	-97.48	5,582
102	5920	Omaha, NE MSA	NE	OMHNE	685,797	41.24	-96.01	4,406
103	5945	Orange County, CA PMSA	CA	OCTCA	2,410,556	33.74	-117.87	948
104	5960	Orlando, FL MSA	FL	ORDFL	1,224,844	28.58	-81.42	4,012
105	6080	Pensacola, FL MSA	FL	PENFL	344,406	30.50	-87.21	2,049
106	6120	Peoria-Pekin, IL MSA	IL	PEOIL	358,552	40.69	-89.56	2,518
107	6160	Philadelphia, PA-NJ PMSA	PA	PHIPA	4,856,963	40.06	-75.24	3,585
108	6200	Phoenix-Mesa, AZ MSA	AZ	PHOAZ	2,238,498	33.47	-111.99	14,598
109	6280	Pittsburgh, PA MSA	PA	PITPA	2,468,289	40.42	-79.93	5,343
110	6440	Portland-Vancouver, OR-WA PMSA	OR	POROR	1,523,741	45.51	-122.68	6,818
111	6480	Providence-Fall River-Warwick, RI MSA	RI	PVDRI	1,509,789	41.78	-71.40	2,236
112	6520	Provo-Orem, UT MSA	UT	PRVUT	269,407	40.26	-111.70	5,547
113	6640	Raleigh-Durham-Chapel Hill, NC MSA	NC	RLGNC	888,665	35.83	-78.74	3,959
114	6680	Reading, PA MSA	PA	RDGPA	336,523	40.37	-75.91	866
115	6720	Reno, NV MSA	NV	RENNV	257,193	39.53	-119.80	6,815
116	6760	Richmond, VA MSA	VA	RCHVA	949,244	37.50	-77.49	5,842
117	6780	Riverside-San Bernardino, CA PMSA	CA	RVRCA	2,588,793	34.01	-117.21	27,408
118	6840	Rochester, NY MSA	NY	ROCNY	1,002,410	43.11	-77.61	4,870
119	6880	Rockford, IL MSA	IL	RFDIL	283,719	42.26	-89.07	801
120	6920	Sacramento, CA PMSA	CA	SACCA	1,481,220	38.64	-121.28	5,309
121	6960	Saginaw-Midland, MI MSA	MI	SGNMI	211,946	43.51	-84.04	816
122	7040	St. Louis, MO-IL MSA	MO	SLSMO	2,580,720	38.64	-90.35	8,844
123	7080	Salem, OR PMSA	OR	SLMOR	278,024	44.95	-123.00	1,938
124	7120	Salinas, CA MSA	CA	SLNCA	355,660	36.62	-121.67	3,771
125	7160	Salt Lake City-Ogden, UT MSA	UT	SLCUT	1,119,874	40.80	-111.93	11,881
126	7240	San Antonio, TX MSA	TX	SANTX	1,407,745	29.48	-98.47	7,385
127	7320	San Diego, CA MSA	CA	SDGCA	2,498,016	32.88	-117.11	4,526
128	7360	San Francisco, CA PMSA	CA	SFRCA	1,603,678	37.71	-122.41	1,801
129	7400	San Jose, CA PMSA	CA	SJSCA	1,534,274	37.32	-121.91	2,695
130	7480	Santa Barbara-Santa Maria-Lompoc, CA MSA	CA	SBRCA	369,608	34.62	-120.07	3,789
131	7500	Santa Rosa, CA PMSA	CA	SRSCA	388,222	38.41	-122.72	1,768
132	7510	Sarasota-Bradenton, FL MSA	FL	SARFL	489,483	27.34	-82.50	1,618
133	7560	Scranton–Wilkes-Barre–Hazleton, PA MSA	PA	SCRPA	575,322	41.28	-75.88	1,776
134	7600	Seattle-Bellevue-Everett, WA PMSA	WA	SEAWA	1,972,933	47.65	-122.23	4,503
135	7680	Shreveport-Bossier City, LA MSA	LA	SHRLA	359,687	32.52	-93.72	2,698
136	7800	South Bend, IN MSA	IN	SBDIN	296,529	41.68	-86.23	969

1 First three characters indicate locale name and last two chracters indicate state name

2 Land area of locales measured in square miles

This table reports 205 locales but the TransNet methodology models only 204 where the Evansville, IN MSA is discarded since no data for this locale is reported by the 1995 ATS

Table 10: Geographic & Demographic Data Used in TransNet, Base Year = 1990 (Continued)

No	METCODE	METNAME	STPOST	MSAID [1]	POP	LAT	LON	AREA [2]
137	7840	Spokane, WA MSA	WA	SPKWA	361,333	47.68	-117.37	1,781
138	7920	Springfield, MO MSA	MO	SPRMO	298,818	37.17	-93.26	3,021
139	8000	Springfield, MA MSA	MA	SPRMA	672,970	42.17	-72.57	1,904
140	8120	Stockton-Lodi, CA MSA	CA	STKCA	480,628	37.94	-121.29	1,426
141	8160	Syracuse, NY MSA	NY	SYRNY	659,924	43.10	-76.19	2,779
142	8200	Tacoma, WA PMSA	WA	TACWA	586,203	47.18	-122.42	1,807
143	8240	Tallahassee, FL MSA	FL	TALFL	259,107	30.49	-84.32	2,603
144	8280	Tampa-St. Petersburg-Clearwater, FL MSA	FL	TMPFL	2,067,959	28.02	-82.56	3,331
145	8400	Toledo, OH MSA	OH	TOLOH	654,157	41.61	-83.64	2,209
146	8480	Trenton, NJ PMSA	NJ	TRTNJ	325,824	40.26	-74.70	229
147	8520	Tucson, AZ MSA	AZ	TUCAZ	666,957	32.23	-110.96	9,189
148	8560	Tulsa, OK MSA	OK	TULOK	761,019	36.13	-95.92	6,460
149	8680	Utica-Rome, NY MSA	NY	UTINY	316,645	43.13	-75.28	2,715
150	8720	Vallejo-Fairfield-Napa, CA PMSA	CA	VALCA	339,471	38.26	-122.14	1,695
151	8735	Ventura, CA PMSA	CA	VTRCA	669,016	34.24	-119.03	2,208
152	8840	Washington, DC-MD-VA PMSA	DC	WASDC	4,122,259	38.83	-77.16	6,028
153	8960	West Palm Beach-Boca Raton, FL MSA	FL	WPBFL	863,503	26.61	-80.14	2,386
154	9040	Wichita, KS MSA	KS	WICKS	511,111	37.71	-97.31	4,181
155	9160	Wilmington, DE PMSA	DE	WMTDE	578,587	39.69	-75.67	1,284
156	9240	Worcester, MA PMSA	MA	WCTMA	709,705	42.23	-71.82	1,579
157	9280	York, PA MSA	PA	YRKPA	339,574	39.94	-76.75	910
158	9320	Youngstown-Warren, OH MSA	OH	YTWOH	613,622	41.07	-80.73	1,741
159	9999	Non-MSA AL	AL	NMTAL	1,364,595	33.00	-86.77	34970
160	9999	Non-MSA AR	AR	NMTAR	1,463,076	35.08	-92.58	45519
161	9999	Non-MSA AZ	AZ	NMTAZ	789,124	33.37	-111.83	89730
162	9999	Non-MSA CA	CA	NMTCA	1,266,534	35.46	-119.36	68855
163	9999	Non-MSA CO	CO	NMTCO	607,659	39.50	-105.20	88105
164	9999	Non-MSA CT	CT	NMTCT	221,011	41.49	-72.87	1352
165	9999	Non-MSA DE	DE	NMTDE	87,413	39.40	-75.56	842
166	9999	Non-MSA FL	FL	NMTFL	1,183,910	27.80	-81.63	24433
167	9999	Non-MSA GA	GA	NMTGA	2,212,055	33.33	-83.87	46021
168	9999	Non-MSA IA	IA	NMTIA	1,420,293	41.96	-93.05	48351
169	9999	Non-MSA ID	ID	NMTID	801,225	44.24	-115.13	81692
170	9999	Non-MSA IL	IL	NMTIL	1,290,726	41.28	-88.38	40653
171	9999	Non-MSA IN	IN	NMTIN	1,925,939	40.16	-86.26	25082
172	9999	Non-MSA KS	KS	NMTKS	361,677	38.45	-96.54	73633
173	9999	Non-MSA KY	KY	NMTKY	2,296,721	37.81	-85.24	35520
174	9999	Non-MSA LA	LA	NMTLA	1,285,116	30.70	-91.46	31592
175	9999	Non-MSA MA	MA	NMTMA	543,530	42.27	-71.36	2954
176	9999	Non-MSA MD	MD	NMTMD	2,175,792	39.15	-76.80	5953
177	9999	Non-MSA ME	ME	NMTME	835,833	44.31	-69.72	29728
178	9999	Non-MSA MI	MI	NMTMI	1,849,402	42.87	-84.17	44333
179	9999	Non-MSA MN	MN	NMTMN	1,373,613	45.21	-93.58	64181
180	9999	Non-MSA MO	MO	NMTMO	535,656	38.44	-92.15	54968
181	9999	Non-MSA MS	MS	NMTMS	1,865,236	32.57	-89.59	42760
182	9999	Non-MSA MT	MT	NMTMT	607,890	46.81	-111.21	140219
183	9999	Non-MSA NC	NC	NMTNC	2,739,914	35.55	-79.67	35991
184	9999	Non-MSA ND	ND	NMTND	331,190	47.38	-99.33	61168
185	9999	Non-MSA NE	NE	NMTNE	746,097	41.18	-97.40	74117
186	9999	Non-MSA NH	NH	NMTNH	557,056	43.15	-71.46	7800
187	9999	Non-MSA NJ	NJ	NMTNJ	1,284,685	40.44	-74.43	2046
188	9999	Non-MSA NM	NM	NMTNM	781,870	34.62	-106.34	114364
189	9999	Non-MSA NV	NV	NMTNV	205,874	37.17	-116.30	95573
190	9999	Non-MSA NY	NY	NMTNY	414,920	41.51	-74.65	24520
191	9999	Non-MSA OH	OH	NMTOH	2,090,511	40.48	-82.75	24932
192	9999	Non-MSA OK	OK	NMTOK	1,309,986	35.60	-96.83	57277
193	9999	Non-MSA OR	OR	NMTOR	894,833	44.73	-122.58	82988
194	9999	Non-MSA PA	PA	NMTPA	585,419	40.46	-77.08	21834
195	9999	Non-MSA SC	SC	NMTSC	1,626,393	34.03	-81.03	22443
196	9999	Non-MSA SD	SD	NMTSD	490,848	44.05	-99.04	72299
197	9999	Non-MSA TN	TN	NMTTN	1,188,733	35.80	-86.40	25292
198	9999	Non-MSA TX	TX	NMTTX	3,081,478	30.94	-97.39	215125
199	9999	Non-MSA UT	UT	NMTUT	387,183	40.44	-111.90	78528
200	9999	Non-MSA VA	VA	NMTVA	3,318,759	37.75	-77.84	30893
201	9999	Non-MSA VT	VT	NMTVT	431,561	44.08	-72.81	8816
202	9999	Non-MSA WA	WA	NMTWA	890,814	47.34	-121.62	47776
203	9999	Non-MSA WI	WI	NMTWI	78,419	43.73	-89.00	42441
204	9999	Non-MSA WV	WV	NMTWV	921,547	38.77	-80.82	18868
205	9999	Non-MSA WY	WY	NMTWY	319,632	42.68	-107.01	89079

1 First three characters indicate locale name and last two characters indicate state name

2 Land area of locales measured in square miles

This table reports 205 locales but the TransNet methodology models only 204 where the Evansville, IN MSA is discarded since no data for this locale is reported by the 1995 ATS

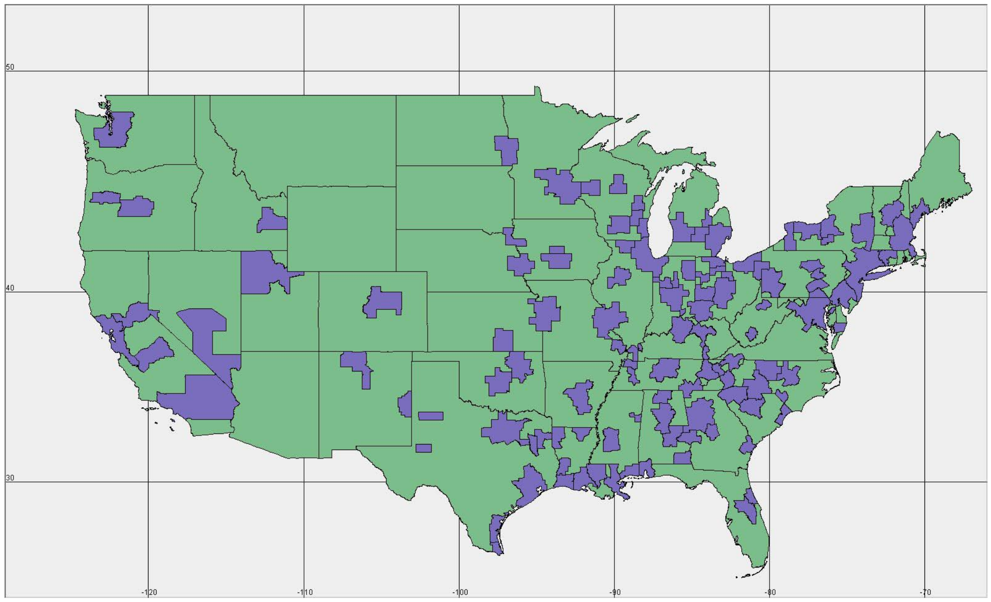


Figure 13: Spatially Explicit Representation of CONUS via MSA and Non-MSA Locale

4.2.2 The Airport Network Model

The NAS network model serves as the backbone for the transportation supply model of TransNet. The first step in constructing this model is to down-select the over 3000 airports in the CONUS to a more manageable list of airports. A report by the Federal Aviation Administration (2001) on the total passenger enplanements at commercial service airports in the United States for year 2001 as extracted from the Air Carrier Activity Information System was used to perform this task. This report showed that the 31 large hub airports, 36 medium hub airports, 69 small hub airports, and 266 non-hub airports within the FAA-NPIAS system serviced 69.3 percent, 19.8 percent, 7.6 percent, and 3.2 percent of the total passenger enplanements respectively. Since 99.9 percent of the total passenger enplanements are serviced by these 402 primary airports, it is safe to say that these airports fully capture the transportation activities in the NAS and can be used as the basis for formulating the NAS network model.

To further reduce the size of this airport list, airports that are located in Alaska, Hawaii, Puerto Rico, and the Virgin Islands are removed. The MSA locale in which each airport is located at is determined. Airports that are not located within any of these 204 locales are airports that are located in MSAs that were not considered by the ATS report. There are 80 such airports and they collectively contributed to 1.9 percent of the total enplaned passengers in 2001. These airports are tagged with a flag MSA[ST] where [ST] is the two-letter state code for the states in which the airports are located. While the contribution towards total passenger enplanements by these airports is not large, many of these airports could service the transportation demand of consumers in the 47 non-MSA locales and are therefore included in this study. Subsequently, the finalized airport list for constructing the TransNet NAS network model consists of 273 primary airports and are depicted in Figure 14.

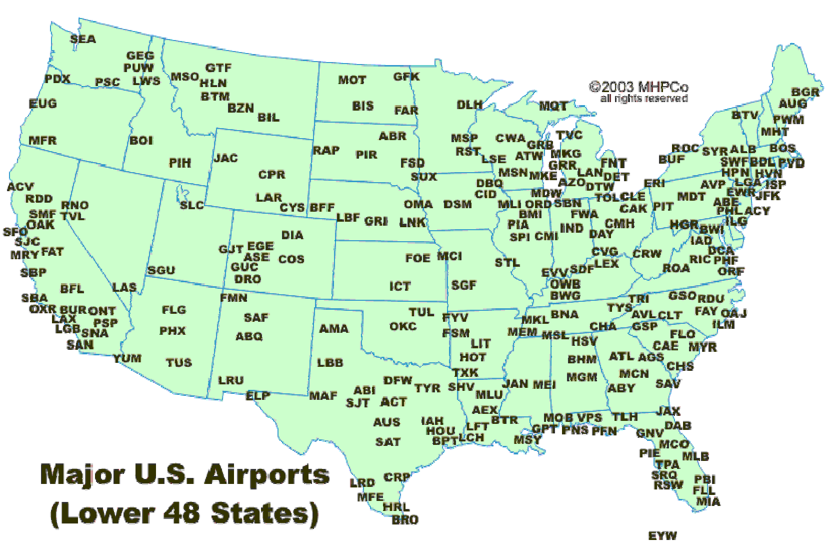


Figure 14: Airport Distribution in the NAS Network Model [Source: Wheatley Memorial Institute]

Table 11: Baseline Service Providers and Segment Operations

Code	Service Provider Name	Num Segments	% Contribution
US	US Airways Inc.	710	17.65%
DL	Delta Air Lines Inc.	599	14.89%
AA	American Airlines Inc.	498	12.38%
UA	United Air Lines Inc.	444	11.04%
NW	Northwest Airlines Inc.	345	8.58%
CO	Continental Air Lines Inc.	271	6.74%
TW	Trans World Airways LLC	194	4.82%
WN	Southwest Airlines Co.	150	3.73%
EA	Eastern Air Lines Inc.	146	3.63%
HP	America West Airlines Inc.	141	3.51%
OE	Westair Airlines Inc.	116	2.88%
QX	Horizon Air	101	2.51%
ML	Midway Airlines Inc.	84	2.09%
PA	Pan American World Airways	69	1.72%
ZW	Air Wisconsin Airlines Corp	58	1.44%
AS	Alaska Airlines Inc.	56	1.39%
YX	Midwest Airline, Inc.	26	0.65%
APN	Aspen Airways Inc.	8	0.20%
TB	USAir Shuttle	4	0.10%
MG	Champion Air	2	0.05%
Total		4022	100.00%

The next step in constructing the NAS network model is to populate flight segments that link any two of these 273 airports. Historical flight segment data extracted from the FAA's T-100 database[2] were used to populate the baseline flight segments for TransNet. Before that, several preprocessing conditions are imposed to reduce the size of the queried operations such that the network model is not overwhelmed by the volume of the data. First, only domestic flights (dictated by field $Region = D$ in the database) will be considered. Second, only flight segments with at least 30 enplanements in a month (field $DepPerformed \geq 30$) will be considered. Third, only scheduled passenger (field $Class = F$) will be considered. Lastly, a representative month is randomly selected for the database query. The month of May in year 1995 was arbitrarily selected for the query, which resulted in 4,022 flight segments serviced by 20 service providers as shown in Table 11.

After populating the baseline flight segment, several locales in TransNet do not

[2]The T-100 database is documented on a monthly basis.

have air transportation services either due to the reasons that i) none of the 273 designated airports are located in those locale or ii) none of the queried flight segments qualified the aforementioned preprocessing conditions. A *reconnecting approach* was formulated to reconnect these previously unconnected locales through nearby airports. The main assumption made was that consumer agents will only choose to reconnect through the 31 large primary hub airports and the 36 medium primary hub airport within 200 miles of the locale population centroid. With this assumption, a *neighboring airport list* was constructed based on the shortest greater circle distance to the unconnected locale. The list was further sorted by selecting only the large and medium primary hub airports within 200 miles. Subsequently, route options involving the top three neighboring airports were offered for servicing trip requests from consumer agents originating from and going to unconnected locales. This simple technique was also used to expand the route options for all consumer agents by enabling aviation trips to be made to and from neighboring airports. This concept is an integral part of the endeavor to address the impact of intermodal and multimodal relationships at the larger NTS level, as discussed in the next section.

For the purpose of forecasting the demand-supply interactions, a capacity limit was imposed on each of the airports modeled. This capacity limit was determined based on the maximum allowable arrivals and departures per hour reported by the Administration (2004). The capacity benchmark values for the top 35 airports are provided in Appendix F. An upper and lower limit is reported for the capacity levels and there are two weather conditions for this report: Optimum condition represents good weather with visual separation and Marginal condition represents weather not good for visual approaches but better than instrument flight rules. Undoubtedly, weather has a large influence on the actual capacity level of airports at a given time period, also known as the *airport called rates*. Thus, depending on the airport location and its vulnerability to weather conditions, the airport called rates may be as high as the Optimum rate or lower than the Instrument Flight Rule (IFR) rate but typically averages in between these two rates. The lower limits for the Optimum condition benchmark capacity values were selected as the capacity limits since they are neither too optimistic nor too conservative in forecasting future capacity levels at the top 35 airports. Since the baseline flight segment were extracted at the daily basis, the capacity limit was also aggregated at the daily level by multiplying the selected capacity level by 15 hours a day[3].

4.2.3 Doorstep-to-Destination Transportation Model

The motivation behind addressing intermodal and multimodal relationships at the larger NTS level was presented in Literature Review. These two transportation system-of-systems relationships are briefly revisited here to initiate the discussions of tasks involving the implementation of these relationships. Intermodal relationships can be defined as the *reinforcing interactions* between different transportation modes in completing *different trip segments*. For example, a traveler who is planning to take a commercial flight must first employ a ground transportation mode to go from the origin location to the departure airport, and possibly from the arrival airport to the destination location as well. On the other hand, multimodal relationships can be defined as the *competing interactions* between different transportation modes in completing *the same trip segment*. For example, a traveler can choose between commercial air carriers and personal automobile to travel between any two origin and destination locations as longs as the mode options are available.

The implementation of intermodal relationship in TransNet is driven by the doorstep

[3]FAA charts flight operations for 15 hours a day from 7 AM to 10 PM local time.

to destination concept[4]. The gist behind this concept lies in determining the time and cost expended at the secondary legs (doorstep-to-airport and airport-to-destination) of a trip. This includes the consideration for wait times at airports in the computation for total trip time. The mode options for these secondary legs in an air transportation research may be personal or rental automobiles and commercial ground services such as taxi and transit. Intuitively, the mode choice for a secondary leg has no significant impact on the overall trip time, cost, and other psychological factors in choosing between one airline flight over another. The doorstep to destination concept is depicted in Figure 15; showing the utilization of ground transportation modes for completing the secondary legs.

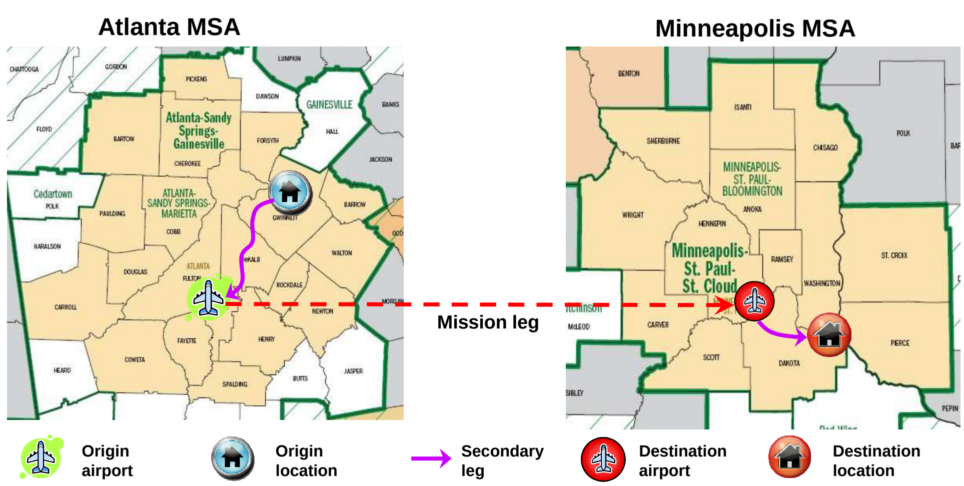


Figure 15: Doorstep-to-Destination Intermodal Relationship - Atlanta MSA to Minneapolis MSA Example

When multimodal relationships are considered in the research, the mode choice for the mission leg could now be either commercial air transports or personal automobiles. The block speed for air transportation modes and personal automobiles

[4]The doorstep-to-destination concept was heavily employed in the Personal Air Vehicle (PAV) research that the author has worked on as documented in DeLaurentis et al., 2004)

as perceived by consumers are probabilistically sampled from triangular distributions $\triangle\{400, 425, 450 \text{ mph}\}$ and $\triangle\{50, 55, 60 \text{ mph}\}$ respectively. These block speed values are used to compute the perceived travel time for a trip, which along with a perceived trip cost are used to perform a preliminary mode selection process.

The actual travel time via these modes are computed by the corresponding service provider based on the class of the aircraft used. The flight distance is computed from as the greater circle distance of the two given coordinate points. Throughout the analysis, the ground driving distance is estimated to be 1.25 times the greater circle distance. With these estimations, the travel cost is calculated as the product of driving distance and an assumed per mile cost of vehicle operations. The additional costs of overnight stays on long distance ground trips are also considered. While this approach must be posed as a completely different mode choice selection problem, the impact of intermodal relationships on the mode choice selection for the mission leg is still minimal apart from the fact that the doorstep-to-destination concept will no longer require access to airports when personal automobiles are selected for the mission leg. When then does intermodal relationship becomes significant?

Intermodal transportation relationship becomes significant when the consumer agent has the option to travel via neighboring airports located in other locales as facilitated by the reconnecting approach discussed earlier. Under such circumstances, the fare differences due to i) different operating costs (largely due to cheaper landing fees at secondary airports), ii) different route options offered, and iii) different choices of service provider altogether allow Consumeragents to choose more selectively. At the same time, the access distance to airports increases significantly enough to influence the mode choice selection between ground and air modes for the mission leg. Therefore, by extending the reconnecting approach to explore possibilities for the Consumeragent to depart from alternative large hub airports within driving distance, the concurrent considerations of both intermodal and multimodal relationships become meaningful and begin to reflect more realistic travel demand and mode choice selection behaviors. Such travel patterns are more eminent for consumer agents in locales that are located in the vicinity of large primary hub airports such as Macon GA (to Atlanta GA), Nassau-Suffolk NY (to New York City NY), and Peoria IL (to Chicago IL). This alternative airport concept is depicted in Figure 16.

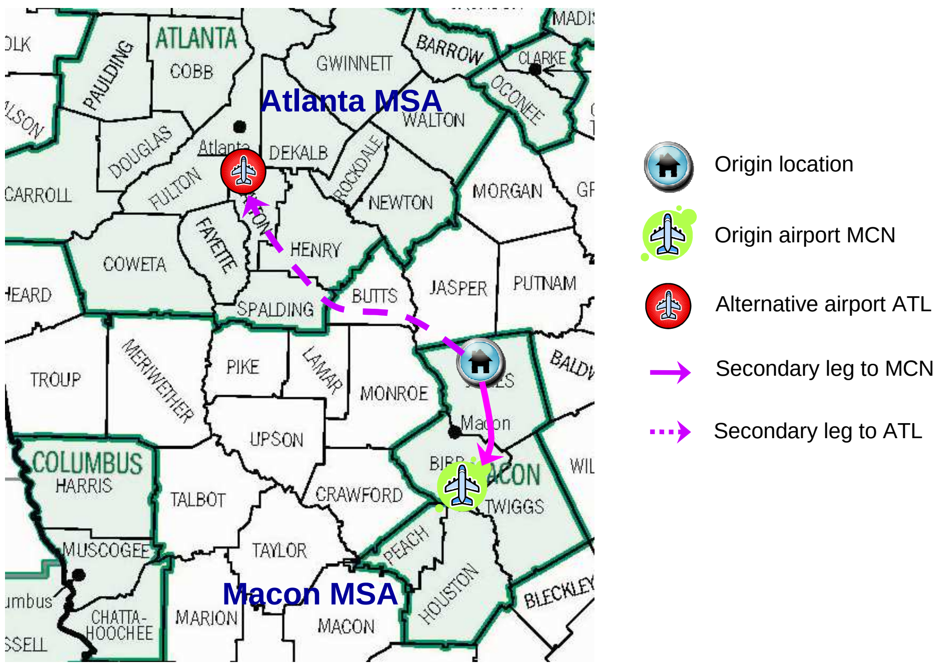


Figure 16: Alternative Airport Route Selection Approach - Macon MSA Example

Since the exact location of the alternative airport is known, the distance and subsequently travel time expended at the secondary legs of a trip can be computed. Personal automobiles, taxis, and rental automobiles are the viable ground mode options available at the secondary legs (rental automobiles are available only at the destination location). Once again, the access distance to and from the airports will have a major impact on determining this secondary travel cost and time, which eventually will influence the multimodal mode selection process.

4.3 Integrative Demand-Supply Model

No existing research has reported a sound methodology for concurrently analyzing transportation demand and transportation supply components. The TransNet model attempts to reduce this research gap beginning with the independent yet concurrent construction of the transportation demand and supply models at the microscopic level, where consumer agents and service provider agents represent the operative entity behind each model respectively. Hence, transportation activities are derived at the microscopic level and are modeled as simulated processes that are interwoven within the structures of these two models. The microscopic transportation activities serves as the constituents of the TransNet simulation model and when aggregated yield the virtual transportation environment of the NAS.

The model architecture for the TransNet integrative demand-supply framework is first introduced in Section 3.4. The implementation of the transportation demand model represented by Consumeragents and the transportation supply model represented by Servprovagents are discussed in Sections 4.3.1 and 4.3.2 respectively. Finally, the transportation activities simulated as the resultants of these two interacting models are documented in Section 4.3.3.

4.3.1 Transportation Demand via Consumer Agents

4.3.1.1 Overview

Mobility, as observed throughout history, started off as the byproduct of the search for food, water, and shelter for human and animals alike; perhaps even one of the key drivers of human civilization. While time has deviated our intent for mobility away from plain survival needs, the author strongly believes that mobility will always remain as one of the deeply-rooted fundamental human needs.

Transportation demand is one of the primary derivatives of mobility and thus, serves as one of the pillars in this research along with transportation supply-side components. The primary goal of modeling transportation demand, whether real or hypothetical, present or future, is to deduce demand properties in terms of volume, growth, and/or trends. There are various approaches for modeling this highly complex system, each with different pros and cons and emphasizing different demand properties. Transportation demand modeling in TransNet adopts the bottom-up approach via the Agent-Based Modeling and Simulation (ABM/S) technique, using microscopic consumer agents as the the constituents of demand generation. By adopting this technique, the most critical pre-requisite for generating trip demand is to ensure that the probabilistically generated consumer agents accurately represent the collective consumer market segments within the transportation environment in study.

4.3.1.2 Consumer Agent Definition

Consumer agents can be viewed as individual-based models of human travelers with the primary responsibility of generating trip demand and deciding on the transportation mode for executing each trip. Following this description, there is a substantial level of individualism in determining the purpose and profile of the generated trips. Thus, each consumer agent is *unique* in the sense that it possesses a unique set of properties that governs its geographic location, income level, and propensity to spend on travel needs. Consumer agents are further categorized into household agents and enterprise agents, each of which is designed to generate personal and business trips respectively. Personal trips can be further divided into personal business and leisure trips in compliance to the categorization chosen by the 1995 ATS. Households instead of individuals are used as the representative of travel demand for several reasons. First, long distance trips frequently have more than one traveling individual and under such circumstance, travel decisions are almost always made collectively as a household. Second, the reduced number of agents required significantly eases the computational burden of this large scale simulation model.

Much of the discussions on agent definition provided below followed the modeling approach reported by Lewe (2005) while using methods and techniques from the conventional Four Step Model. Consumer agents are probabilistically displaced into the aforementioned locales of the spatially-explicit TransNet transportation environment based on the national demographic landscape. Besides locale placement, the other highly important agent characteristic that differentiates between consumer agents and the trips they generate is the consumers' income. This is because the trip frequency and transportation mode choice are dependent on the agents' income based on a mobility budget space concept. From a object-oriented modeling perspective, *Consumeragents* are created to represent these household and enterprise consumer agents.

Placement of agents

The first and most important parameter in the population of household and enterprise agents is the origin locale placement because it determines the volume and distribution of the generated trips in the simulation. Since households and enterprises represent Consumeragents in TransNet, the number of households and business establishments throughout the 204 TransNet locales served as the probability density function for determining the origin locale of household and enterprise agents respectively. The number of households is obtained from the U.S. Census database. The number of business establishments in MSA and non-MSA locales are obtained from U.S. Census Bureau (1997) and Office of Advocacy (1999) respectively. There are a total of 93.3 million households and 6.18 million business establishments in the U.S. in 1990.

Consumer agents that are populated in non-MSA locales have their origin coordinates (latitude and longitude) specified using the non-MSA agent displacement method described in Section 4.2.1. This method assumes the agent displacement boundary in the shape of a circle centered at the population centroid and computes the radius, R for this displacement boundary based on the land area. A displacement path determines the origin location for the Consumeragent as a straight line away from the population centroid defined by a displacement radius and angle. This displacement radius and is sampled from a triangular distribution $\triangle\{0, \frac{R}{2}, R \text{ miles}\}$ in unit miles. and a uniformly sampled displacement angle. With this coordinate-specific origin location, distance from the secondary leg can then be computed. This method, shown in Figure 17, is similarly employed for determining the origin coordinates of Consumeragents that are populated in MSA locales as well as destination coordinates for all trips. The significance of this method is that it provides a stochastic approximation for distances to and from airports without incurring the high computational cost of distributing Consumeragents at a finer level of granularity such as county or even zip code.

Income distribution model

One of the key features that make this consumer distinguishable from other consumers is the consumer's income level. This household income value directly influences the trip frequency and transportation mode choice selection of the Consumeragent from a trip utility perspective, which is further discussed in the next section. The primary objective here is such that the household income values assigned to the Consumeragents in a locale can best paint the socio-economic picture of the population in that locale and further develop the individualism of each Consumeragent. Rather than using generic single-point values such as the mean income, a unique income

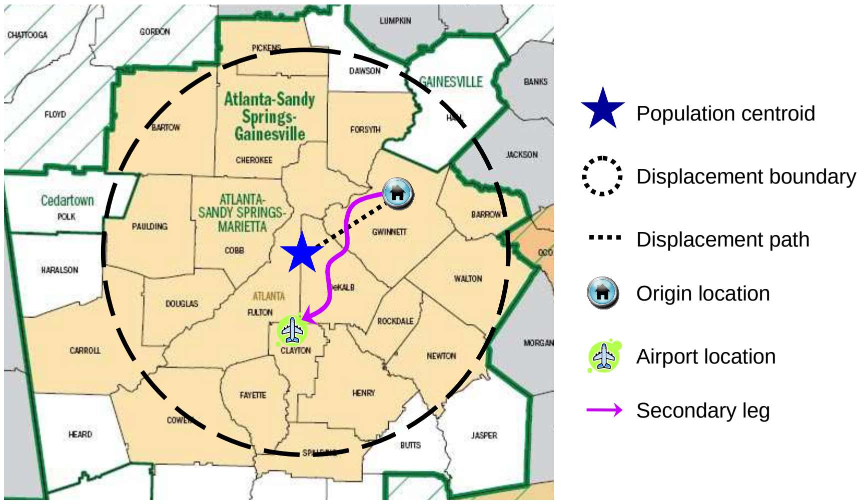
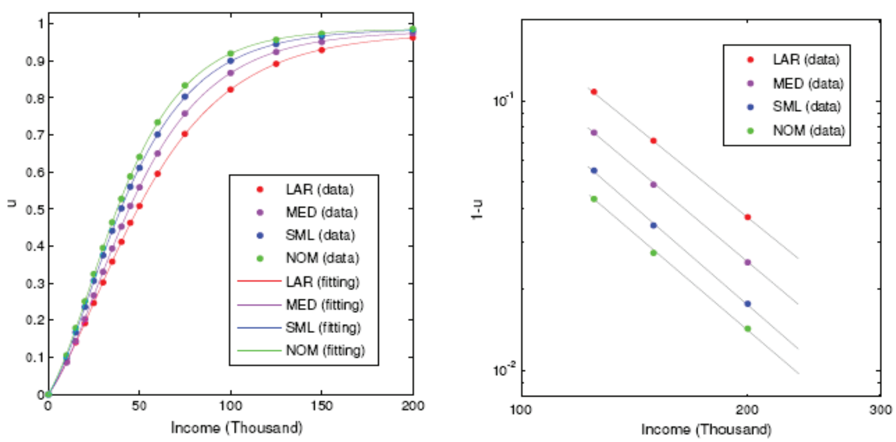


Figure 17: MSA Consumer Agents Probabilistic Displacement Method

value is sampled from an income distribution model that is unique to the origin locale of the Consumeragent. The income distribution model is developed translating historical income distributions of each specific locale into a continuous cumulative distribution function. Therefore, the two steps for obtaining these income distribution models are i)to obtain historical income distribution data and ii) to statistically fit the data into a closed form mathematical function such that income values can be assigned to the agent population without discontinuities.

The raw data was obtained from the Office of Economic Affairs, Economic, and Market Analysis Division (2005). Acquiring raw income distribution data and retrofitting the data for the specific TransNet locales, both MSA and non-MSA, required rigorous efforts. Thus, the final income distributions are tabulated in Appendix F for reference purposes. The next step of fitting the data into a close form equation is performed next. Lewe (2005) reported that income distribution is well-fitted to a piece-wise function of the Richards growth model for the lower income groups and a Pareto model for the higher income groups, as shown in Figure 18. The parameters for fitting the income distributions into the Richards growth curve function (β_i) shown in Equation 6 are determined. Solution for income is then analytically solved as Equation 7. These income distribution models for specific locales are then tested by generating simulated income values via Monte Carlo Simulation and re-matching them against the raw data. The final income distribution model parameters as tabulated in Appendix F. A *trip income* concept is used to distinguish the impact of monetary factors on personal and business trips and is discussed in Section 4.3.1.3.



(a) Richards Model

(b) Pareto Model

Figure 18: Household Income Polynomial Fitting Equation [Source: Lewe (2005, p.143)]

$$Y = (1 - \beta_1 e^{-\beta_2 \kappa}) \frac{1}{1 - \beta_3} \tag{6}$$

where Y = Distribution percentile

κ = Income

β_i = Calibration parameters

$$\kappa = -\frac{1}{\beta_2}\ln[\frac{1}{\beta_1} - (\frac{Y}{\beta_1})^{1-\beta_3}] \tag{7}$$

$$\text{where } \kappa = \text{Income}$$

$$Y = \text{Distribution percentile}$$

$$\beta_i = \text{Calibration parameters}$$

4.3.1.3 Trip Generation

From a modeling perspective, desired *wishlist* trips are first generated for Consumeragents at the beginning of the simulation tick. A wishlist trip that falls within the feasible mobility budget space is converted into an actual trip demand also known as an *executed* trip. The time and cost utilization of this executed trip is recorded, which reduces the remaining mobility budget for the Consumeragent to carry out future trips. The set of desired wishlist trips are executed one at a time until a maximum allowable trip threshold is exceeded. For this study, the mean cost threshold is assumed to be four percent of the consumer's household income. The mobility cost threshold for a Consumeragent is then sampled from a triangular distribution centered at this mean value with a plus and minus 20 percent variability. The mobility time threshold for a Consumeragent is sampled with the same variability, but the mean time threshold is less specific from agent to agent; starting with an arbitrary baseline value of 100 hours a year and progressively adjusted based on the actual time spent by consumers during the pre-simulation calibration.

The profile of each type of trips (personal and business) is identically distributed using the probabilistic trip generation process. From an object-oriented modeling perspective, *Tripobjects* are created to represent these trips by Consumeragents. The

Table 12: Batch Size Distribution for Enterprise Agents

Batch size	1	2	3	4	5	6
Percent	62.65	22.20	7.29	4.23	2.16	1.08

general trip attributes are first discussed followed by the assumptions and characterizations for ground and air transportation modes.

General trip attributes

Each generated Tripobject from the Consumeragent has a certain degree of independence and uniqueness such that the individualism characteristic of human travelers can be retained and the strength of the ABM/S method can be fully harnessed. Apart from the trip destination, other trip parameters that make up the profile of a trip includes batch size, trip tick, and advance purchase period.

The batch size for household agents and enterprise agents are determined differently. It is assumed that the batch size for personal trips would be equal to the household size, that is, all the household members make the trip. Subsequently, a household size distribution is obtained from the Census database. The same assumption cannot be made for enterprise agents as household size does not apply to business trips. While the Census database does not collect batch sizes for business trips, the batch size distribution for enterprise agents are extracted from the 1995 ATS database, as shown in Table 12.

A *trip income* concept is conceived to distinguish the impact of monetary factors on personal and business trips. The trip income for a personal trip is simply the household income since the household income includes all possible income sources for the traveling household. The trip income for business trips would need to consider the batch size of the trip as each traveling individual contributes to the trip income independently. Hence, two main assumptions are made to determine the trip income for business trips. First, the household income of each traveling individual is probabilistically sampled from a triangular distribution with a mean value equals to the household income of the primary enterprise agent and a plus and minus 30 percent variability to the primary household income. Second, the personal income of each traveling individual is assumed as a fraction of its household income and this fraction is computed as the quotient of one over the mean number of earners for its household income bracket as reported by the U.S. Census Bureau. The mean number of earners with respect to income brackets is excerpted from Housing and Household Economics Statistics (1995) and tabulated in Table 13. Subsequently, the trip income for a business trip is the sum of personal incomes of all traveling individuals. This treatment of trip income not only reinforced the individualism of consumers and their travel demand, it also created a more realistic representation of the higher value of time for business travelers through the time and cost utility of trip to be discussed later.

The trip tick is sampled from different data sources depending on the time tick size prescribed for the problem. A monthly time tick is recommended as travel patterns and seasonal factors are always observed on a monthly basis. The Bureau of Transportation Statistics published reports from year 2000 to 2002, which provides in-depth analysis of certain highlighted transportation indicators that describe the transportation industry in the U.S. (Johnson, 2002). Seasonality factor based on a monthly usage percentage, as shown in Table 14, are available from this reporting effort and are used to distribute trip ticks.

Advanced purchase period is one of the most dominant factors in determining airline ticket price. Real world airlines learnt to be proficient at mining the immense amount of demand data from years of operations in order to yield insights into the

Table 13: 1995 Mean Earners per Household by Household Income

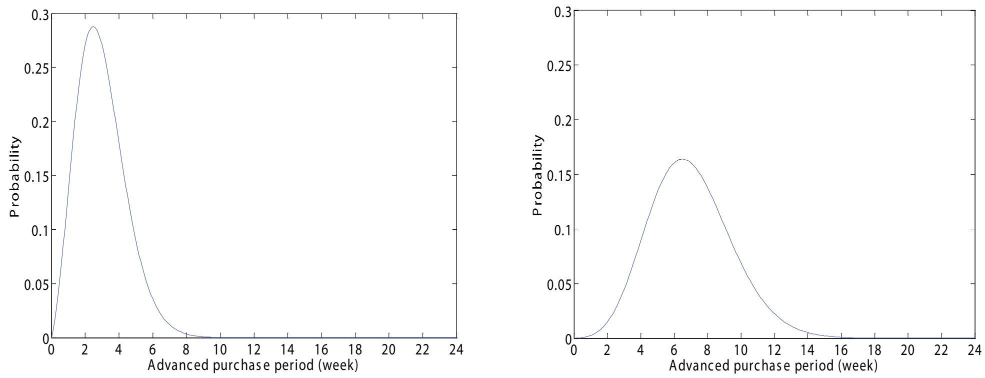
Income Brackets	Mean Earners
Under $2,500	0.31
$2,500 to $4,999	0.48
$5,000 to $7,499	0.36
$7,500 to $9,999	0.47
$10,000 to $12,499	0.60
$12,500 to $14,999	0.71
$15,000 to $17,499	0.85
$17,500 to $19,999	0.94
$20,000 to $22,499	1.09
$22,500 to $24,999	1.17
$25,000 to $27,499	1.23
$27,500 to $29,999	1.32
$30,000 to $32,499	1.40
$32,500 to $34,999	1.46
$35,000 to $37,499	1.54
$37,500 to $39,999	1.61
$40,000 to $42,499	1.62
$42,500 to $44,999	1.74
$45,000 to $47,499	1.75
$47,500 to $49,999	1.83
$50,000 to $52,499	1.84
$52,500 to $54,999	1.91
$55,000 to $57,499	1.88
$57,500 to $59,999	1.96
$60,000 to $62,499	1.93
$62,500 to $64,999	2.06
$65,000 to $67,499	2.08
$67,500 to $69,999	2.18
$70,000 to $72,499	2.15
$72,500 to $74,999	2.16
$75,000 to $77,499	2.03
$77,500 to $79,999	2.15
$80,000 to $82,499	2.17
$82,500 to $84,999	2.24
$85,000 to $87,499	2.21
$87,500 to $89,999	2.24
$90,000 to $92,499	2.19
$92,500 to $94,999	2.25
$95,000 to $97,499	2.27
$97,500 to $99,999	2.26
$100,000 and over	2.20

Table 14: U.S. Transportation Seasonality Factor Based on Monthly Usage Percentage

Month	Monthly usage percentage
January	0.0721
February	0.0720
March	0.0808
April	0.0802
May	0.0831
June	0.0911
July	0.0966
August	0.0983
September	0.0846
October	0.0834
November	0.0781
December	0.0796
Total	1.0000

air travel demand function. Without the luxury of such data, many existing research on airline pricing assumed a known and fixed demand function for air travel demand oftentimes in the form of a Poisson distribution (Botimer and Belobaba, 1999). Commonly used for representing arrival process, the Poisson distribution needs to be assigned only one parameter, that is, the mean arrival time. Using this approach to determine the advance purchase periods for consumers, purchases for business trips and personal trips are assumed to arrive 2 weeks and 6 weeks before the actual travel date respectively. The plots of both Poisson distributions are shown in Figure 19.

The value for perceived wait time at airports is probabilistically sampled for each Consumeragent using perceived wait times reported by the 2003 Omnibus Household Survey (Omnibus, 2003), as shown in Table 15. The assignment of this value allows for unique total travel time computation when the mode choice selection model is invoked by the Consumeragent. In addition, Consumeragents are able to consider nearby airports as the departing origin location of their trips. Finally, the number



(a) Business Trips **(b) Personal Trips**

Figure 19: Poisson Distributions for Sampling Advanced Purchase Period

Table 15: Probability of Airport Perceived Wait Times

Perceived wait time (minutes)	30	45	75	105	135
Probability (%)	3	24	23	37	13

of trips executed by any given Consumeragent is dictated by the mobility budget space concept. The mobility budget space thresholds are directly dependent on the agents' household income; reiterating the importance of the aforementioned approach for assigning unique household income values to Consumeragents.

Ground transportation modes

Several assumptions were made prior to computing the trip information for ground transportation modes.

1. The driving distance is assumed to be 1.25 times the greater circle distance computed from the coordinates at the origin and destination locations.

2. The automobile block speed for each Consumeragent is probabilistically sampled from a triangular distribution $\triangle\{50, 55, 60 \text{ mph}\}$.

3. An overnight stay with incurred time and cost is added to trips via a piecewise probabilistic

function with respect to travel times as shown below:

$$Prob(\text{overnight}) = \begin{cases} p_1 & \text{if } 4 \leq t < 8 \\ p_2 & \text{if } 8 \leq t < 12 \\ p_3 & \text{if } 12 \leq t < 16 \\ p_4 & \text{if } t \geq 16 \end{cases} \quad \text{where } t = \text{travel time in unit hours} \tag{8}$$

Apart from the assumptions made above, several special treatments were prescribed for these computations based on commonly observed travel patterns and behaviors that are otherwise uncaptured by the conventional time and cost driven utility functions. First, there exists consumers who insist on choosing ground transportation modes for executing trips that are dominated by air transportation mode choices from a utility perspective. Examples of these seemingly *stubborn* ground trips are leisure (cross country) road trips by household Consumeragents and trips carrying fragile goods or heavy machineries by enterprise Consumeragents. A probability for reverting back to selecting ground transportation mode <u>after</u> an air transportation mode is selected is prescribed to implement this behavior. This probability value is assigned to four percent and five percent for business and personal trips respectively. Another treatment was imposed after observing the stark difference between the automobile cost per mile value for household and enterprise Consumeragents. The automobile cost for personal trips, which predominantly covers the cost of fuel, is given as USD 0.096 per statute mile. Meanwhile, the automobile cost for business trips, which for most business entities, follows the U.S. Internal Revenue Service (IRS) compensation rate is given as USD 0.30 per statute mile. Depending on the type and size of the business entity, it may be more realistic at times for an enterprise Consumeragent to analyze the driving cost largely based on the cost of fuel. Thus, five percent of enterprise Consumeragents are assumed to be more inclined at using USD 0.096 for computing the ground transportation mode choice instead of the IRS compensation rate.

Air transportation modes

Following the doorstep-to-destination concept, the mission profile for air transportation modes was decomposed into the mission and secondary ground legs. The mission leg refers to the actual trip distance traversed from the origin access point to the destination access point. The aircraft block speed was determined based on the aircraft class employed by the route option made to the consumer. Given the exact locations of the origin and destination airports, the mission leg distance and subsequently the travel time can be computed.

The secondary ground leg refers to the trip distance traversed from the origin location to the origin access point and from the destination access point to the destination location. The intermodal ground mode options available are personal automobiles, taxi, and rental automobile. Rental cars are made available only at the destination location. The cost of utilizing personal automobiles was calculated based on the aforementioned USD 0.096 per statute mile cost of operation. The cost of utilizing rental automobiles was fixed at a national average of USD 31.25 per rental. Meanwhile, the cost of utilizing taxis was computed from a standard taxi fare structure with an average fixed first mile cost (USD 2.36) followed by a per mile cost (USD 2.04) of vehicle operations. Since secondary ground legs are performed locally within a given locale (i.e. in-city driving), the automobile block speed was assumed to be 40 percent less than the block speed used for computing long distance ground trips.

A special treatment was implemented; aimed at highlighting the fact that the destination locations for business trips are typically closer to the population centroid location since business entities tend to be drawn towards the center of consumer activities. Hence, the secondary leg ground distance for enterprise Consumeragents were assumed to be 75 percent of the actual computed secondary leg distance.

The consideration of secondary legs of an aviation trip is a direct implementation of the intermodal transportation relationships, which as discussed earlier, play a significant role in allowing the use of vicinity airports as the departing origin and in providing a more concise characterization of the trip mission profile.

4.3.1.4 Trip Distribution

The trip destination is one of the most important trip-related characteristics as it eventually determines demand patterns and subsequently the service provider network for the modeled transportation environment. Lim et al. (2006) and Lim et al. (2007) have used the trip counts in the O-D matrix extracted from the 1995 ATS as the probability density function for distributing trips at the MSA level. Since this database remained the best data source for studying aggregated travel behavior of Americans, it is used also as the main calibration data source for the model validation. Subsequently, it is a well recommended practice in modeling and simulation to refrain from being overly reliant on the calibration data source for model construction as this would dilute the veracity of the underlying model construct even when the calibration data matches. Furthermore, significant data anomalies have been observed at the O-D market level as discussed in Appendix A.7. For the purpose of distributing trips, erroneous counts on total produced and attracted trips at the O-D market level make the data source highly ill-suited for distributing trip demand and calls for a better solution. Hence, the Gravity Model approach discussed in Section 3.3 was employed to develop a gravity-based trip distribution model.

Gravity-based trip distribution model

After studying the conventional methods for distributing transportation demand, the

Gravity Model has been selected because the underlying attractor-impedance functions in the model is highly suitable for distinguishing between different locales; providing the level of uniqueness that is sought for in this spatially-explicit representation of the CONUS. More specifically, the doubly constrained gravity model derived from Equation 1 was developed. This hypothetical trip distribution model needs to be constructed from historically observed total produced trips (P_i) and total attracted trips (A_j) for each of the 204 locales. Unfortunately, the only data source for P_i and A_j at this level of granularity remains to be the 1995 ATS, where erroneous P_i and A_j data was evidently observed for certain locales. A pre-processing treatment was performed on the data to remedy this concern.

The pre-processing treatment is formulated by focusing on total produced trips P_i, which is hypothesized to be mathematically explained as a function of population and income levels. Subsequently, a polynomial equation in the form depicted in Equation 9 is posed as the governing equation for P_i.

$$P_i = \beta_0 (POP^{\beta_1}) (\frac{INC_k}{1000}^{\beta_2}) \tag{9}$$

$$\begin{aligned} \text{where } POP &= \text{Population count} \\ INC_k &= \text{Income level at } k^{th} \text{ percentile} \\ \beta &= \text{Calibration parameters} \end{aligned}$$

Using income values at various percentile levels, a non-linear regression is performed on the hypothetical model and compared against the observed P_i data from the 1995 ATS. The initial comparison highlighted a total of nine distinct outliers, all of which belonged to non-MSA locales. This reinforced the argument made on the exorbitant trip volumes reported for non-MSA locales by the 1995 ATS. After removing these outliers, the best explanatory results is obtained as shown in Figure 20 when 70^{th} percentile income level is used and with β_0, β_1, and β_2 approaching the

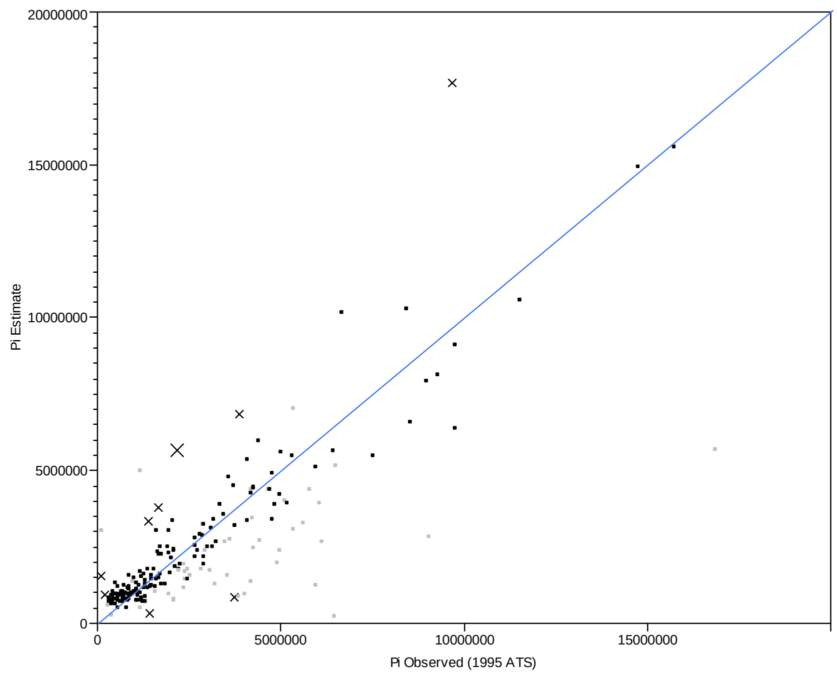


Figure 20: Model Fit for Hypothetical Total Produced Trips

values of 1.0, 1.0, and 0.5 respectively. This surprisingly well-behaved β values shows that the total produced trip does indeed has a simple and direct relationship with population and income levels.

With the calibrated model above, total produced trip values can be estimated for all locales including the initially removed outlier locales. To proceed to the next step of estimating the corresponding total attracted trip values for each locale, it is assumed that the $\frac{P_i}{A_j}$ ratio is retained from the 1995 ATS and thus, A_j is nothing but the product of this ratio and the estimated P_i. With these P_i and A_j values, the gravity-based trip distribution model can now be executed.

The cost function F_{ij} from Equation 1 was assumed as: $F_{ij} = e^{-\gamma \text{Trip Distance}}$ where $\gamma = 0.8$ yielded the trip distribution matrix that best satisfied the first hypothesized condition discussed in Section 3.4. Subsequently, this trip distribution matrix is used as the trip distribution O-D matrix for all other calibration and simulation runs.

4.3.1.5 Mode Choice Selection Model

The final responsibility of Consumeragents is to decide on the transportation mode choice for executing the trip. Two levels of selection are prescribed. The preliminary selection is a simplistic mode choice selection for determining if certain trips will most certainly be carried out by personal automobiles. The Nested Multinomial Tournament Logit Model performs the much more intricate multimodal mode choice selection.

Preliminary mode choice selection

The 2001 National Household Travel Survey conducted by the U.S. DOT-BTS reported that over 97 percent of long distance person trips less than 300 roundtrip miles are performed by personal vehicles. Understandably, the utilization of air transportation modes increases as the trip distance increases, as shown in Table 16. While this reinforced the notion that multimodal relationship between ground and air transportation modes is important in the longer term study of the evolution of mobility, it also highlighted the fact that the proportion of trips utilizing personal vehicles is much greater than those utilizing air transportation modes to the point that some trips can be assumed to *most certainly* utilize personal automobiles to service the travel demand. Thus, the purpose of implementing a preliminary mode selection process is to identify trips that will most certainly employ personal vehicles for servicing the travel demand.

The preliminary mode selection process employs the Pareto efficiency concept, which allows for Consumeragents to outright prefer and select one mode choice over another without making the other alternative worse off. Barring the impact of intangible factors such as fear of flight or long distance driving, the primary reason for consumers to choose commercial air services over driving is the travel time savings

Table 16: Long Distance Trips Composition by Mode and Distance

Miles	100-299	300-499	500-999	1000-1999	2000+	Total
Personal vehicles [1]	97.20%	94.30%	85.90%	53.90%	22.20%	89.50%
Air	0.20%	1.50%	10.30%	42.40%	74.80%	7.40%
Bus	1.60%	3.40%	3.20%	2.60%	1.40%	2.10%
Train	0.90%	0.70%	0.60%	0.90%	0.80%	0.80%
Other	0.20%	0.10%	0.00%	0.10%	0.80%	0.20%

1 Personal vehicles include cars, pickup trucks, or sports utility vehicle
Source: 2001 National Household Travel Survey, U.S. DOT-BTS

at the expense of likely higher travel costs. Hence, in scenarios when commercial air services cost more yet do not provide time savings, which is more frequently observed in the current transportation system with longer security lines and longer take-off queues, Consumeragents would immediately deem these trips are *certainly ground* trips. The block speed for air transportation modes and personal automobiles *as perceived by consumers* are probabilistically sampled from triangular distributions $\triangle\{400, 425, 450 \text{ mph}\}$ and $\triangle\{50, 55, 60 \text{ mph}\}$ respectively. A simplified service provider model is developed to solely generate air fares for the simulated trip demand via a polynomial pricing function that was regressed from historical air fares data as shown in Equation 10 below (Lewe, 2005).

$$P = 86 + 0.177 \times d - 0.0000246 \times d^2 \qquad (10)$$

$$\text{where } d = \text{ airport-airport flight distance}$$

A trip code flag was used to identify these *pre-selected* trips such that these trips will automatically bypass the multimodal mode choice selection process in the simulation. This preliminary mode choice selection process has been shown to reduce the number of trips that need to be considered for multimodal mode choice selection by at least 40% and thereby reduced the computational burden of the model by an equal portion.

Nested Multinomial Logit Model

The choice mechanism that consumers adopt to make travel decisions are implemented with utility theory and multinomial logit (MNL) model. Utility theory postulates that an individual chooses the alternative that offers the highest utility. The outcome of this systematic utility function (V) is a numerical representation of the attractiveness of each transportation mode choice to the traveler, which ultimately reflects the traveler's decision making behavior. Synonymously, we can model the traveler's decision making behavior by computing the *disutility function*, since it is easier to capture the negative entities (cost and time spent) rather than the positive entities (cost and time saved) of the trip. In other words, the traveler assigns a disutility (D) of each mode choice by considering the cost (c) and travel time (t) as well as his/her value of time spent on traveling, which is defined in Equation 11.

$$D(t,c) = -V(t,c) = T_c + v_t * T_t \tag{11}$$

$$\begin{aligned} \text{where } v_t &= \text{Value of time} \\ T_c &= \text{Trip costs} \\ T_t &= \text{Trip time} \end{aligned}$$

With this disutility function, the probability of selecting each transportation mode choice is obtained using the MNL model. This model probabilistically selects a transportation mode choice based on the disutilities of all transportation mode choices. Equation 12 is modified to include a selection logic calibration constant, α, to better match the predicted and observed modal split data. The initial value for α is 0.001 and the final value after calibrating the mode selection model is 0.018 as reported in

Section 5.

$$P(mode_i) = \frac{e^{\alpha V(mode_i)}}{\sum_{j=1}^{n} e^{\alpha V(mode_j)}} \tag{12}$$

$$\begin{aligned} \text{where } U &= \text{Utility function} \\ n &= \text{Number of mode choices} \\ \alpha &= \text{Calibration constant} \end{aligned}$$

The nested MNL model is conceived from the hierarchical structure of the consumers' decision making process in conjunction with the concept of a tournament logit model developed by Lewe (2005). As shown in Figure 21, the hierarchical structure exists because a service provider can legitimately provide multiple offers for the same trip to a consumer. The tournament logit model postulates that a *champion* is to be chosen for each individual service provider before all the champions are entered into a higher level tournament to crown the ultimate winner, that is, the final transportation mode choice. With this nested MNL model in place, the probability of selecting any given transportation mode choice will be strictly based on the time and cost performance of all transportation modes; unbiased against the number of trip offers posed by each competing service provider. This model is another feature of the methodology to capture behavioral sentience of Consumeragents, in this case, at the transportation mode choice selection process.

4.3.2 Transportation Supply via Service Provider Agents

4.3.2.1 Overview

Undoubtedly, the airline industry is at the heart of the CATS, made up of various blends of airlines or air service providers of different sizes and business models; operating strategies, route maps, and market targets to name the least. Air service providers

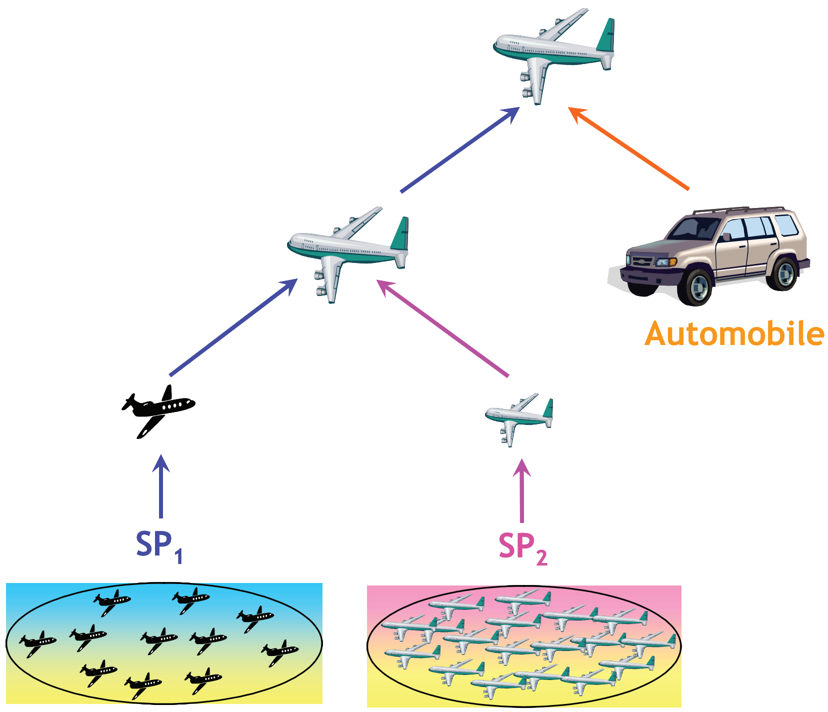


Figure 21: Nested Multinomial Tournament Logit Model

constitutes the supply-side component of the CATS and are thus, the second pillar for the research discussed in this thesis.

As mentioned earlier, an air service provider in the real world is a highly intertwined and complicated assembly of business units, each performing unique functions and possessing unique goals and constraints. Four core functions of service providers are identified: routing, fleet/frequency selection, pricing, and revenue management. Modeling a full-scale air service provider business model is a daunting task that is perhaps beyond the capability of any one individual. Thus, this bottom-up TransNet methodology implemented a representative replication of the air service provider's business model by focusing on routing and pricing while also considering the dynamic pricing aspect of revenue management. The ultimate purpose of this supply model is to facilitate the last two steps in the Four Step Model: mode selection and route selection.

4.3.2.2 Service Provider Agent Definition

Distinguishing characteristics & core functions

A discussion on the service provider agent definition is provided before formally discussing the core functions of these agents as modeled in TransNet. Service provider agents are first categorized by the carrier type. There are multiple ways to perform this categorization, whether based on size differences (for eg., major, national, and regional carriers), business model differences (for eg., legacy and low cost carriers), or even by niche market (for eg., fully-schedule, on-demand, and charters carriers). As a first step towards the analysis, carriers' revenue passengers and available seats data was queried from the FAA T-100 database for year 1995 for all carriers operating in the CONUS. Besides computing the market share from the revenue passengers data, the average load factor (revenue passengers/available seats) is also presented in Table 17 below. This data is further grouped using size and route coverages (4 groups of carriers: major, national, large regional, and medium regional carriers) as the categorization criteria to obtain Table 18.

The comparisons between legacy and low cost carriers is the most actively discussed agenda in the attempt to describe the currently observed hub-and-spokes NAS and to an extent for deciphering the competition in the airline industry. While Table 18 demonstrated that over 90 percent of the NAS demand in the CONUS is serviced by major carriers, this categorization is inapt since both legacy and low cost carriers are labeled as major carriers under the categorization of carrier size. Conveniently enough, the classification of legacy carriers (American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, United Airlines, and US Airways) has not changed

Table 17: 1995 Market Shares and Average Load Factors

Carrier ID	**Carrier Name**	**Carrier Type**	**Market Share %**	**Average Load Factor**
DL	Delta Air Lines Inc.	3	21.38%	60.85%
UA	United Air Lines Inc.	3	15.30%	67.95%
WN	Southwest Airlines Co.	3	11.97%	63.99%
AA	American Airlines Inc.	3	11.37%	64.45%
US	USAir	3	10.41%	61.87%
NW	Northwest Airlines Inc.	3	6.71%	64.49%
CO	Continental Air Lines Inc.	3	3.98%	60.11%
TW	Trans World Airlines Inc.	3	4.38%	61.35%
HP	America West Airlines Inc.	3	2.86%	65.71%
AS	Alaska Airlines Inc.	3	2.58%	61.19%
J7	Valujet Airlines Inc.	2	1.41%	68.83%
QQ	Reno Air Inc.	2	0.97%	63.19%
MQ	Simmons Airlines	2	0.78%	55.11%
EV	Atlantic Southeast Airlines	2	0.79%	45.95%
QX	Horizon Air	2	0.61%	60.05%
XE	Expressjet Airlines Inc.	2	0.37%	47.67%
TZ	American Trans Air Inc.	2	0.39%	62.55%
YV	Mesa Airlines Inc.	2	0.36%	46.97%
AX	Trans States Airlines	2	0.35%	48.65%
ZW	Air Wisconsin Airlines Corp	2	0.30%	52.42%
KP	Kiwi International	1	0.29%	52.45%
WV	Air South Inc.	1	0.29%	49.91%
BF	Markair Inc.	2	0.37%	62.38%
YX	Midwest Express Airlines	2	0.19%	60.68%
KW	Carnival Air Lines Inc.	2	0.23%	64.55%
HQ (1)	Business Express	2	0.15%	39.72%
JI	Midway Airlines Inc.	2	0.12%	49.08%
TB	USAir Shuttle	2	0.11%	41.32%
F9	Frontier Airlines Inc.	1	0.18%	50.26%
NJ	Vanguard Airlines Inc.	1	0.19%	51.98%
W7	Western Pacific Airlines	2	0.10%	62.37%
FF	Tower Air Inc.	2	0.10%	74.63%
NK	Spirit Air Lines	1	0.10%	82.78%
U2	UFS Inc.	1	0.07%	45.27%
FL	AirTran Airways Corporation	1	0.05%	57.42%
OW	Executive Airlines	2	0.04%	47.05%
XP	Casino Express	4	0.03%	85.81%
QD	Grand Airways Inc.	1	0.03%	64.60%
N5 (1)	Nations Air Express Inc.	1	0.02%	47.56%
HA	Hawaiian Airlines Inc.	2	0.03%	55.88%
T3	Tristar Airlines Inc.	1	0.03%	32.28%
W9	Eastwind Airlines Inc.	4	>0.01%	50.38%
A7 (1)	Air 21	1	>0.01%	67.54%
OI	Paradise Airways	1	>0.01%	13.28%
FDQ	Great American Airways	1	>0.01%	60.90%
MG	MGM Grand Air Inc.	1	>0.01%	21.43%
Total			**100.00%**	**55.98%**

Carrier types: 1-Large regional, 2-National, 3-Major, 4-Medium regional
Source: Federal Aviation Administration T-100 Database

Table 18: 1995 Market Shares and Average Load Factors by Carrier Size

Carrier Group	Market Share %	Average Load Factor
Large Regional Carriers	1.26%	52.23%
National Carriers	7.77%	56.39%
Major Carriers	90.94%	63.35%
Medium Regional Carriers	0.04%	79.08%
Total	**100.00%**	**62.58%**

since its inception[5]. However, the classification of low cost carriers remained vague as the low cost operating strategies exists in many regional, national, and major carriers alike. Subsequently, all non-legacy carriers are collectively grouped as the second carrier type under the name of low cost carriers based on the observation that low cost strategies are present in many ways within the operations of these carriers. Thus, the two groups of carrier type identified for modeling TransNet service provider agents are legacy carrier type and low cost carrier type (encompassing all non-legacy carriers). In 1995, legacy carriers owned 67.1 percent of the demand market share while low cost carriers owned the remaining 32.9 percent.

Branching off from this specification, the finance-based and operation-based attributes are defined for the service provider agents. Finance-based attributes include parameters and policies involving operating costs and pricing. Operating costs for service providers are typically divided into direct operating cost (DOC) and indirect operating cost (IOC) components. The magnitude and proportion of these cost components are different for the two carrier types due to several reasons, one of which is that the different carrier types operate different mix of aircraft types and equipage.

[5] During the timeframe of this research, the airline industry faces drastic structural changes beginning with the merger announcement between Delta Airlines and Northwest Airlines in April 2008, which was eventually approved in October 2008. Other legacy carriers have frantically attempted similar moves in what seems to be an inevitable consolidation phase for the troubled industry.

The labor cost components for the two carriers are also significantly different. In addition, when penetrating an O-D market, low cost carriers tend to utilize secondary airports with lower landing fees whenever possible while legacy carriers utilize mostly the large hub airports. There are also significant distinctions in the market segmentation of the two carrier types, resulting in various cost-sensitive service levels offered by each carrier type for a given seat class.

To model the operating cost structure of each carrier type, the operating cost data for the different aircraft types used by both legacy and low cost carriers must be obtained from existing FAA airline reporting data. The mix of aircraft types used by carriers in the real world must also be reduced to a more manageable collection of aircraft classes. The Form 41 Traffic (more commonly known as the T-100), Form 41 Financial Report Schedule P-52, and Form 41 Financial Report Schedule P-7 databases are jointly used to obtain the aircraft data, *DOC* data, and *IOC* data respectively. The T-100 database provides the average flight distance, average seat capacity, and total ramp to ramp utilization minutes of all aircraft types for all reporting carriers. The Schedule P-52 database provides detailed *DOC* breakdown at the aircraft type level with consistent reference with the aircraft types in T-100. The Schedule P-7 database provides detailed *IOC* breakdown at the individual carrier level. These cost components breakdown are tabulated in Table 19.

The *DOC* for a flight segment is measured in dollars per utilization minute, computed by dividing total direct operating costs by the total ramp to ramp utilization minutes. After series of analysis using data years 1990, 1995, 2000, and 2005, the grouping of aircraft types by carrier type and then by average seat capacity seemed to provide the best collective measurements of *DOC* per utilization minute. To allow better comparison of data, a Consumer Price Index factor was used to normalize all *DOC* values to year 1990 dollar. The resulting data are shown in Table 20 and Table

Table 19: Direct and Indirect Operating Cost Components

Direct Operating Cost Components
Flying operations - Flying crew salaries, fuels, insurance, etc.
Direct maintenance - Airframes, engines, etc.
Applied maintenance burden
Net obsolescence and deterioration
Depreciation - Flight equipment
Amortization - Flight equipment
Indirect Operating Cost Components
Passenger service - Flight attendant, food, and other inflight
Aircraft servicing - Landing fee, line servicing, and control
Traffic (passenger, baggage, and cargo) servicing
Reservation and sales
Advertising and publicity expenses
General and administrative expenses
Depreciation - Maintenance equipment
Amortization - Non-flight equipment

Source: Form 41 Schedule P-52 and P-7 databases, U.S. DOT-BTS

Table 20: Direct Operating Cost per Utilization Minute for Seat-based Aircraft Classes (in steps of 40 seats) by Carrier type and Year ($/min))

			1990		1995		2000		2005	
Class	**Seats**	**Avg Seat**	**LGC**	**LCC**	**LGC**	**LCC**	**LGC**	**LCC**	**LGC**	**LCC**
1	**0-39**	**20**	15.19	11.30	19.12	8.53	19.38	11.56	19.07	13.26
2	**40-79**	**60**	20.46	27.56	25.86	13.59	29.12	17.79	18.72	19.11
3	**80-119**	**100**	31.82	29.13	25.38	25.22	31.00	30.50	36.55	29.19
4	**120-159**	**140**	35.21	32.48	30.44	24.25	33.88	28.43	36.75	29.29
5	**160-199**	**180**	42.08	43.80	36.66	36.28	38.39	39.26	45.10	38.91
6	**200-239**	**220**	52.51	48.60	38.06	50.33	46.31	54.03	50.55	56.89
7	**240-279**	**260**	73.62	71.72	54.38	53.19	69.98	61.86	62.99	68.99
8	**280-319**	**300**	70.46	80.84	64.27	72.31	78.20	82.27	67.11	87.92
9	**320-359**	**340**	86.44	104.80	73.33	82.37	83.44	100.77	108.62	108.56
10	**360-399**	**380**	96.78	92.37	98.09	108.99	176.45	114.44	119.60	146.71
11	**$\geq$400**	**420**	113.58	102.53	96.15	91.57	155.16	164.16	146.66	189.51

LGC - Legacy carriers, LCC - Low cost carriers
Source: Form 41 Traffic (T-100) & Financial databases, U.S. DOT-BTS

Table 21: Direct Operating Cost per Utilization Minute for Seat-based Aircraft Classes (in steps of 100 seats) by Carrier type and Year ($/min))

			1990		1995		2000		2005	
Class	**Seats**	**Avg Seat**	**LGC**	**LCC**	**LGC**	**LCC**	**LGC**	**LCC**	**LGC**	**LCC**
1	**0-99**	**50**	27.36	18.77	29.22	13.47	40.92	19.27	27.01	26.75
2	**100-199**	**150**	34.92	32.79	35.24	28.93	43.66	38.07	56.07	43.22
3	**200-299**	**250**	67.12	71.72	64.38	60.29	75.70	80.07	83.64	92.75
4	**$\geq$300**	**350**	78.43	96.77	69.37	100.50	180.28	145.60	156.76	156.66

LGC - Legacy carriers, LCC - Low cost carriers
Source: Form 41 Traffic (T-100) & Financial databases, U.S. DOT-BTS

21 for seat-based aircraft classes in steps of 40 seats and 100 seats respectively.

The accumulated data of *DOC* per utilization minute is fitted to an exponential function with respect to the aggregated average seat capacity metric. The regression analysis, as shown in Figure 22, resulted in R-squared values of at least 0.91 and 0.88 for seat-based aircraft class in steps of 40 seats and 100 seats respectively. This shows that one can confidently use seat capacity as the predictor variable for modeling DOC function for both carrier types. In addition, one of the known operation differences between these two types of carriers is that legacy carriers tend to operate larger aircraft especially when servicing their primary hub airports. Meanwhile, low cost carriers tend to operate smaller aircraft for servicing true O-D demand markets with high load factor targets. Based on this characteristic and other operating strategies, one can expect that specialization tends to drive superior expertise and higher operating efficiencies. The plots of this regression analysis demonstrated this fundamental difference between legacy and low cost carriers, where legacy carriers (blue line) consistently showed the ability to operate higher seat capacity aircrafts at a lower DOC per utilization minute than low cost carriers and vice versa, low cost carriers (pink line) consistently showed the ability to operate lower seat capacity aircrafts at a lower DOC per utilization minute than legacy carriers.

While the continuous exponential regression functions may be used for determining the DOC per utilization minute, discretized aircraft classes by average seat capacity would be a better option for defining the DOC structure of the service provider agents. This is because different carriers employ different seat configurations even though they may be operating the same aircraft type with similar operating cost structure. Therefore, the DOC function with four aircraft classes in steps of 100 seats shown in Table 21 is used to represent the DOC structure for the service provider agents in TransNet. The difference in the DOC for the two carrier types is due to several reasons, one of the main reasons being that legacy carriers have higher salary expenses due to higher labor contract costs. The aircraft maintenance expenses for

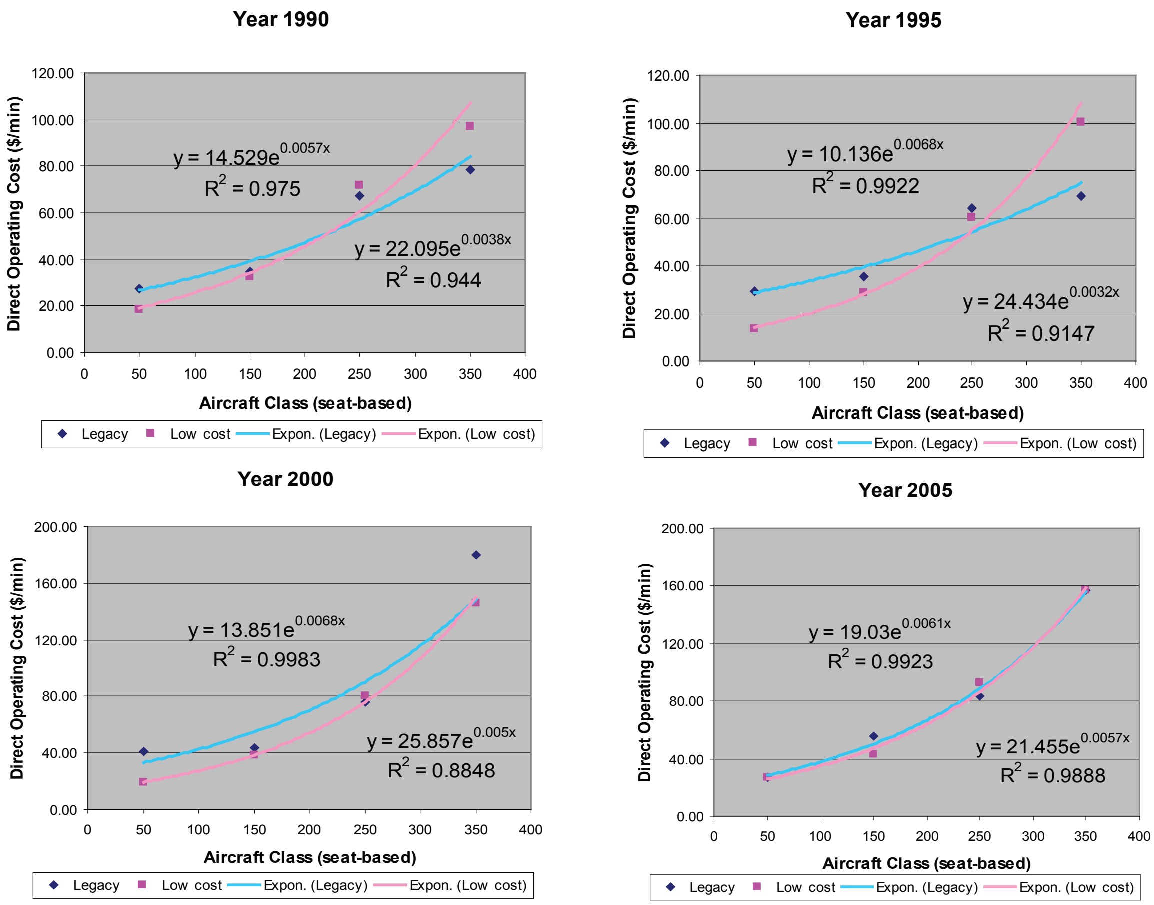


Figure 22: Raw and Regression Data of Direct Operating Cost for Different Aircraft Classes (in steps of 100 seats)

legacy carriers are also higher since they tend to operate larger mixes of aircraft and equipage in comparison with low cost carriers which operate only a handful of common aircraft types. On the other hand, legacy carriers have lower depreciation and amortization expenses since larger portions of the capital costs have been accrued for the older fleet of legacy carriers.

The analysis for the IOC structure is much simpler compared to the DOC analysis as IOC is collectively denoted for each independent carrier rather than for each aircraft type. The IOC components shown in Table 19 can be collected into two forms of variable costs; an Aircraft Servicing IOC (IOC_a measured in dollars per departure) and a Passenger Servicing IOC (IOC_b measured in dollars per passenger). For the baseline year 1990, IOC_a and IOC_b for the six legacy carriers are obtained and the average values are calculated to be \$981 and \$14.78 respectively. Similarly, IOC_a and IOC_b for the low cost carriers are obtained and the average values are calculated to be \$231 and \$9.50 respectively. The staggering difference in the IOC_a between legacy and low cost carriers revealed the stark difference in the business models of these two types of carriers from the cost perspective. Some of the primary causes of this cost difference are the landing fees (low cost carriers tend to avoid primary airports that charges high landing fees), reservation and sales expenses (low cost carriers depends almost entirely on Internet reservations and sales), and general and administrative expenses (commonly coined as the *curse of the incumbents*, legacy carriers incur higher non-flight related expenses due to the geographic coverage and operations scale). The Total Operating Cost (TOC) is then computed as the sum of the DOC and IOC as follows:

$$\begin{aligned} TOC_{flight} =& (\frac{\$DOC}{hour})(\text{Total flight time in hours}) \\ &+ IOC_a + (IOC_b)(\text{Number of passengers}) \end{aligned} \tag{13}$$

A brief description of the pricing parameters and policies for each carrier type is provided next. First and foremost, legacy carriers are known to have more complicated fare structures as compared to low cost carriers. To replicate this observation, legacy carriers are defaulted with 4 fare classes while low cost carriers are defaulted to 2 fare classes. This also translates to a simpler perceived demand function for low cost carrier. A perceived demand function is essentially an $n \times n$ matrix that estimates the consumer's willingness to buy as perceived by service providers. An in-depth explanation of the fundamental construct of the perceived demand function is provided in Section 4.3.2.4 when discussing the pricing subagent. Each fare class holds a percentage discount or premium of a base price determined from the aforementioned cost structure. A variable profit margin which can be changed by the user via an input file declaration is imposed on this base price by both legacy and low cost carriers.

Operation-based attributes are comprised of parameters and policies involving vehicle operations, routing, and other operations-related functions. Many of these parameters and policies are defined by the routing subagent, which generates baseline flight segments and routes using historical operations data from the T-100 database. Within the subagent module is a hub identification algorithm, which identifies hub airports for any one carrier's operations based on the number of connections departing from the airport (denoted as an out-degree in network model lexicon). The seat-based aircraft classes in steps of 100 seats are used to define the aircraft types used by carriers for each specific segment. An average block speed of 500 miles per hour is assumed for all aircraft classes since the vehicle mix in each class is observed to operate close to this speed regardless of seat capacity. The wait time at airports is addressed from the consumer-side as discussed in Section 4.3.1.3.

Having defined these finance and operations attributes, the basic functions of service provider agents can be designed and modeled. The utilization of the integrative demand-supply algorithm (See Section 4.3.3) requires service provider agents to be capable of receiving trip request from a Consumeragent, estimating the trip time and cost, and finally publishing this trip time and cost back to the Consumeragent. Upon mode choice selection by the Consumeragent, the trip outcome will be reported back to the service provider agent in terms of whether or not the trip offer has been accepted. The final function of the service provider agent is then to make adaptive changes to the aforementioned parameters and policies based on the learning mechanism within its subagent.

From an object-oriented modeling perspective, a *Servprovagent* is created to represent a unique air service provider agent. While the aforementioned attribute definitions would sufficiently facilitate the implementation of basic service provider functions, more detailed definitions are required to model the pricing and routing functions of the Servprovagent. Hence, a *subagent* concept is used to improve the fidelity of these two core functions and subsequently, to instill more sentience into these deliberative agents. Subagents are internal entities of an agent that possess individual goals and constraints while remaining affixed towards the top level goals of the agent, much like independent business units within a company. The routing subagent uses historical NAS operations data to generate baseline flight segments and routes, followed by a route generation model and network adaptation model to evolve the route network over time. Meanwhile, the pricing subagent offers the trip fare and time for servicing a trip demand using a dynamic pricing algorithm. These subagent modules are individually discussed next.

4.3.2.3 Routing Subagent

<u>*Overview*</u>

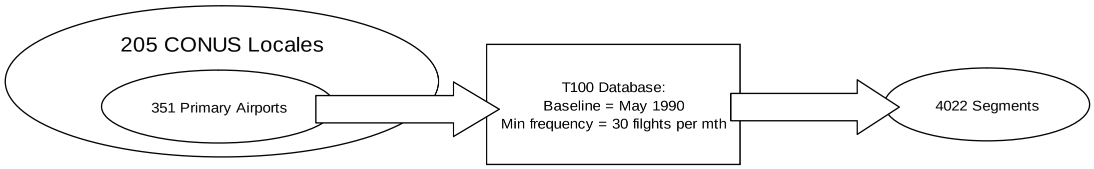
The routing subagent is responsible for creating, assessing, and evolving the route network model for the motherlode service provider agent. Key components within this subagent module are i) a baseline network model that creates the baseline route network from historical NAS operations data, ii) a hub determination algorithm that identifies hubbing activities and the corresponding hub airports from the historical data, iii) a route generation algorithm that generates route options by recombining flight segments at the NAS level, and iv) a network adaptation model that assesses and evolves the route network based on operations performance and demand shifts.

The implementation of these key components utilized many concepts and techniques from the fields of network modeling, graph theory, statistical methods, data manipulation, and airline economics. The key graph theoretic methods used to construct the subagent algorithms are discussed in this section. Please refer to Appendix C for basic introduction to network modeling and graph theory.

Baseline network model

Briefly revisiting the conceptualization of this transportation environment, TransNet represents the CONUS as a collection of 204 MSA and non-MSA locales. Within these locales, there are 273 primary airports which are used as the commercial air transportation access points for the representative NAS model. Both the locales and airports are created as network modeling entities called *nodes*. Flight segments linking these airports and locales are modeled as *edges*. These nodes and edges become the constituting elements on the TransNet baseline network model for the CONUS transportation environment. The Census database and the FAA's National Plan of Integrated Airport Systems (NPIAS) database are concurrently used to provide locale and airport specifications. The NAS operations data for the specified airports is then extracted from the T-100 database. Extracting this large amount of data required rigorous efforts in constructing and synchronizing data entries from the different databases and was unquestionably a critical pre-requisite for obtaining the baseline data sets. May 1995 is arbitrarily selected as the baseline month and year for the operations data extraction. The flight segments are also required to have a minimum frequency of 30 flights per month in order filter out flight segments that has less impact on the overall NAS network. Based on all these specifications and conditions, 4022 flight segments operated by 20 unique carriers were selected to construct the baseline network model.

From the object-oriented modeling perspective, an *Airportobject* is created to



a) Creating baseline flight segments

SEGMENT_ID	ORIG_APT	DEST_APT	CARRIER	FREQUENCY	RECORDED_SEATS	RECORDED_PAX	AIRCRAFT_TYPE
1	ABQ	DFW	AA	33	4686	3988	655
2	ABQ	ORD	AA	91	12922	7587	655
3	ALB	ORD	AA	120	17040	7402	655
4	ALB	RDU	AA	61	7198	3706	710
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

b) Sample flight segment

Figure 23: Baseline Network Model Flow Diagram

represent each of the airports modeled in the TransNet model. A *Segmentobject* with a unique *SEGMENT_ID* is created for each flight segment defined by the column entries shown in Figure 23b. As the column names would intuitively suggest, *ORIG_APT*, *DEST_APT*, and *CARRIER* refer to the (IATA-standardized) origin airport code, destination airport code, and carrier code. *FREQUENCY* refers to the number of departures performed within the given month. *RECORDED_SEATS* and *RECORDED_PAX* refer to the number of available seats and revenue passengers flown for the given month respectively. Lastly, *AIRCRAFT_TYPE* refer to the three-letter aircraft type code used by the FAA to service the flight segment. Each Segmentobject is populated as an edge that links the two nodes representing the origin and destination Airportobjects. The 4022 Segmentobjects that constitute the baseline network model are mapped into two figures depicting the legacy carrier network and the low cost carrier network as shown in Figure 24 and Figure 25. In order to not clutter the CONUS maps with individual MSA and non-MSA locales, the shaded areas in the figures represent Census-defined Combined Statistical Area, which consist of multiple metropolitan or micropolitan areas that have a moderate degree of employment interchange. Besides the fact that the legacy carrier network is much more developed, the presence of hubbing activities can be clearly observed. The low cost carrier network also exhibited some level of hubbing activities since many low cost carriers tend to operate heavily through mini hubs, which will be further discussed next in the hub determination algorithm.

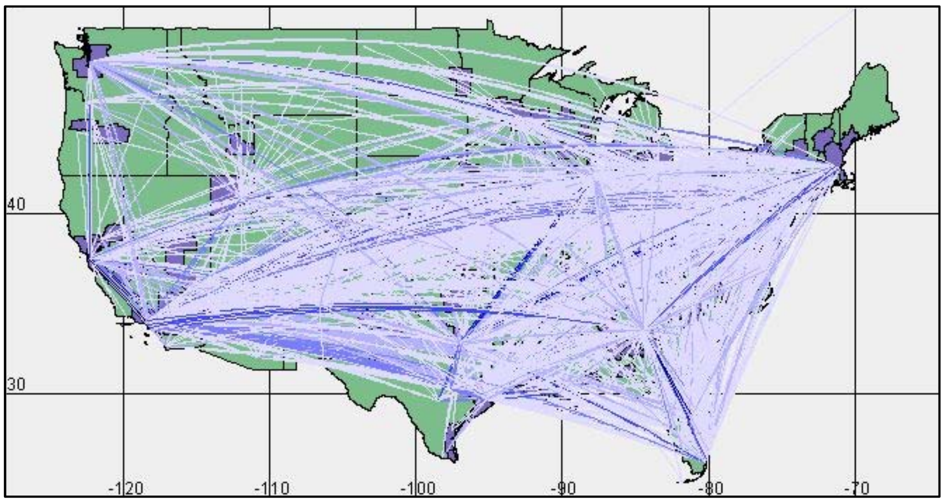


Figure 24: Baseline Network Model: Legacy Carriers

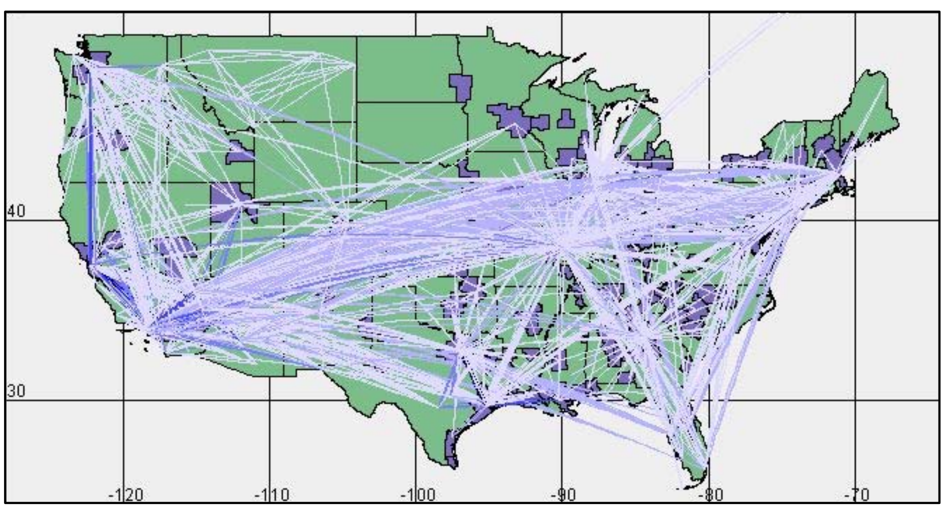


Figure 25: Baseline Network Model: Low Cost Carriers

<u>*Hub determination algorithm*</u>

From a network and object-oriented modeling perspective, a collection of Segmentobjects (edge) that are connected through the same Airportobject (node) constitute a *Routeobject* (a collection of connecting edges), and multiple distinct Routeobjects can exist simultaneously to service the same O-D market through different hub airports. Thus, in order to construct Routeobjects, it is pertinent that the hub airports for a given carrier are identified. Hubbing behavior can be observed from the layout of a network system through several graph theoretic indices. One of the most widely and appropriately used index for measuring hubbing activities is the order degree of a node, which measures the significance of the node in terms of the number of edges that are attached to the node. Hub nodes have a high order degree as many edges converges into it, while terminal points have an order degree that can be as low as one. A perfect hub would have an order degree equals to the summation of all the order degrees of the other nodes in the graph and a perfect spoke would have an order degree of one.

Dwelling more into this graph theoretic concept, Segmentobjects that arrive into an Airportobjects are *in-edges* and those departing from are *out-edges*. The in- and out-degrees (d) for each Airportobject node keep track of the number of unique edges that are connected to and from the node and are updated every time a new edge is formed. Historical data showed that the out-order degree for a given airport is almost always identical to the in-degree, inherently due to the fact that most consumers' long distance travel are symmetric in an aggregated sense. Since this research considers symmetric return trips, only the out-degree of a node is measured to identify hub airports in this algorithm.

The hub determination algorithm begins with the creation of a list of Airportobjects utilized by each unique Servprovagent. Using the out-degree index, this list is ranked from highest to lowest out-degree. Next, a method or metric to approximate the proportion of hubbing activities performed by a carrier is required. The clustering coefficient for the network system was investigated as the first option for guiding this approximation process. As defined in the earlier section, clustering coefficient indicates how close a node and its neighbors are from being a complete graph, thereby implying the concentration of edges in the vicinity of the hub node. Another closely related metric, network density, is also investigated to reveal how well-connected are the nodes in a graph, thereby identifying if a network is a dense point-to-point network. Hence, a higher clustering coefficient suggests a higher proportion of hubbing activities while a higher network density suggests a higher proportion of point-to-point activities.

The analysis of clustering coefficient and network density are performed for the network system of each carrier and for the entire baseline network model and results are tabulated in Table 22. Evidently, the legacy carriers exhibit high clustering coefficients and extremely low network density. Most of the low cost carriers exhibits much lower clustering coefficients compared to the legacy carriers with the exception of Alaska Airlines, America West Airlines, Trans World Airways, and Southwest Airlines, which are known to operate heavily from *mini hubs* servicing high demand O-D market at the regional level.

While the aforementioned graph theoretic indices remain good indicators of hubbing versus point-to-point transportation activities, these metrics do not explicitly approximate the hubbing activities within each network system by specifying the number of nodes at the top of the list that are deemed as hub airports. Therefore, a new metric called *hubbing ratio* is formulated to represent the cumulative contribution of hubbing activities by Airportobjects for a service provider in a list ranked from highest to lowest out- degree. This hubbing ratio at the k^{th} node in an ranked

Table 22: Carriers' Clustering Coefficient and Network Density Analysis

Code	Airline Name	Num Segments	Clustering Coeff.	Density
AA	American Airlines Inc.	498	0.6792	0.0427
APN	Aspen Airways Inc.	8	0.0000	0.3200
AS	Alaska Airlines Inc.	56	0.4972	0.2188
CO	Continental Air Lines Inc.	271	0.4326	0.0469
DL	Delta Air Lines Inc.	599	0.6026	0.0430
EA	Eastern Air Lines Inc.	146	0.1704	0.0449
HP	America West Airlines Inc.	141	0.5022	0.0666
MG	Champion Air	2	0.0000	0.5000
ML	Midway Airlines Inc.	84	0.2581	0.0727
NW	Northwest Airlines Inc.	345	0.4219	0.0332
OE	Westair Airlines Inc.	116	0.1620	0.0719
PA	Pan American World Airways	69	0.2293	0.0947
QX	Horizon Air	101	0.3273	0.1051
TB	USAir Shuttle	4	0.0000	0.4444
TW	Trans World Airways LLC	194	0.3128	0.0374
UA	United Air Lines Inc.	444	0.5342	0.0381
US	US Airways Inc.	710	0.4853	0.0469
WN	Southwest Airlines Co.	150	0.4006	0.1561
YX	Midwest Airline, Inc.	26	0.0000	0.1327
ZW	Air Wisconsin Airlines Corp	58	0.2470	0.0858
Entire TransNet baseline network		4022	0.3940	0.0238

Airport codes as defined by the International Air Transport Association (IATA)

list, indicated as ϕ_k, is defined as:

$$\phi_k = \frac{\sum_{i=0}^{k} d_i}{\sum_{j=0}^{N} d_j} \tag{14}$$

where N = Number of nodes in the ranked list

Legacy carriers are expected to share very similar hubbing ratio. After a close scrutiny of the flight segments data along with references to the clustering coefficients, the hubbing ratio for legacy carriers is approximated to be 55 percent. By perturbing through the ranked airport list for each carrier, airports that contribute to the hubbing activities up to the hubbing ratio value are identified as hub airports. While low cost and regional carriers are not explicitly known for publishing connecting routes to consumers, a low level of hub concentration can be traced to the larger low cost carriers simply due to concentrated services at high demand markets. As a result of high frequency flights in those markets, consumers could potentially create their own connecting routes by combining multiple direct routes as long as they are economically

Table 23: Hub Airports Identified through Cumulative Hubbing Ratio (ϕ) < 55*percent* Based on Operations in May 1990

AA		**CO**		**DL**		**NW**		**UA**		**US**	
Routes = 8713		**Routes = 1362**		**Routes = 5009**		**Routes = 3112**		**Routes = 5375**		**Routes = 4423**	
Apt	Cum ϕ	Apt	Cum ϕ	Apt	Cum ϕ	Apt	Cum ϕ	Apt	Cum ϕ	Apt	Cum ϕ
DFW	16.95%	DEN	15.85%	ATL	14.93%	DTW	19.13%	ORD	20.25%	CLT	11.09%
ORD	30.96%	IAH	30.49%	DFW	26.40%	MSP	37.83%	DEN	32.09%	PIT	20.04%
RDU	38.08%	EWR	42.07%	CVG	35.47%	MEM	48.26%	IAD	39.25%	BWI	24.52%
BNA	43.24%	CLE	49.39%	SLC	43.47%	MKE	50.43%	SFO	44.86%	DAY	29.00%
SJC	45.45%	LAX	53.05%	MCO	46.40%	BOS	52.17%	LAX	47.66%	PHL	32.62%
MIA	47.42%			BOS	48.80%	SEA	53.91%	SEA	49.84%	SFO	35.82%
BOS	48.89%			LAX	50.93%			OAK	51.40%	LAX	39.02%
CLE	50.12%			FLL	52.27%			SMF	52.96%	LGA	41.58%
DCA	51.35%			LGA	53.60%			FSD	54.21%	IND	43.92%
EWR	52.58%			MIA	54.93%					TPA	46.06%
LAX	53.81%									DCA	47.97%
										EWR	49.89%
										MCO	51.39%
										SAN	52.88%
										BOS	54.16%

Airport codes as defined by the International Air Transport Association (IATA)

rational. The results in Table 22 show that the clustering coefficient value varies significantly from one low cost carrier to another. This leads to the assumption that low cost carriers are not likely to share similar hubbing ratios either. Since hubbing activities do not dominate the operational business model of low cost carriers to begin with, the top two nodes ranked by out-degree are conclusively assumed as the mini hubs for all low cost carriers. Using this algorithm, hub/minihub airports identified for legacy carriers and low cost carriers based on operations in May 1990 are tabulated in Table 23 and Table 24.

Table 24: Hub Airports Identified for Low Cost Carriers Based on Operations in May 1990

Airline	**APN**	**AS**	**EA**	**HP**	**MG**	**ML**	**OE**	**PA**	**QX**	**TB**	**TW**	**WN**	**YX**	**ZW**
Routes	6	94	1603	979	2	447	286	132	161	6	2476	210	42	158
Hub 1	DEN	SEA	ATL	PHX	JFK	MDW	SFO	MIA	SEA	LGA	STL	PHX	MKE	ORD
Hub 2	ASE	PDX	DCA	LAS	LAX	PHL	IAD	JFK	BOI	BOS	JFK	HOU	DCA	IAD

Airport codes as defined by the International Air Transport Association (IATA)

Route generation algorithm

The purpose of this algorithm is to generate Routeobjects that can service a given

Tripobject request made by a Consumeragent. There are two subroutines within this algorithm. The first subroutine generates all possible route combinations from flight segments that connect through the previously identified hub airport. This seemingly large number of route combinations is reduced to a more realistic, logical, and computationally manageable size via the algorithm in the second subroutine. This second subroutine, invoked only when a trip request arrives, probabilistically determines if a Routeobject is *feasible* for servicing the trip demand.

This first subroutine generates Routeobjects by matching up Segmentobjects that connects through a common hub Airportobject via an exhaustive search method. It is assumed that only up to one connections is allowed, that is, a Routeobject can be constructed from at most two connected Segmentobjects. This is determined from observations of the U.S. DOT-BTS DB1B data, which revealed that while multiple connections itineraries are not uncommon, a significant portion of air travel in the CONUS is performed with direct and single-connection itineraries. The hub determination algorithm provided a list of identified hub airports ($\overline{H}$) as well as an airport list that is ranked from highest to lowest out-degree ($\overline{O}$). A similar airport list is replicated but ranked from lowest to highest out-degree ($\overline{D}$). All possible Routeobjects are then generated using the algorithm below:

```
For each hub airport, H_m, from H̄
    For each origin airport, O_i, from Ō
    If O_i has in-edge and out-edge to H_m
        For each destination airport, D_j, from D̄
        If O_i ≠ D_j & D_j has in-edge and out-edge to H_m
            Create Routeobject, R(O_i, D_j) that connects O_i → H_m → D_j
```

The second subroutine reduces the list of Routeobjects by examining the feasibility of a given route option. This subroutine is required because of two main issues related to the nature and setup of the problem. First, a Routeobject should be feasible from an operation logistics perspective, that is, the Segmentobjects that create this Routeobject must operate in such a way that connecting them to service a true O-D demand would make logical sense. An example of an illogical route option is one that services a trip demand from New York to Chicago via a hub airport in Los Angeles, therefore incurring unreasonable total flight time. The first subroutine does not filter out these infeasible route options.

Second, the *FREQUENCY*, *RECORDED_SEATS* and *RECORDED_PAX* information for Segmentobjects are aggregated at the monthly basis in order to be consistent with the lowest level of granularity for the simulation time tick. This implies that there are no flight schedule information to explicitly connect the departure timetables of any two segment fligths that make up a route option. Thus, the second subroutine also served as a probabilistic meta-model for connecting segment flights where instead of generating flights with specific timetables to create a Routeobject, Segmentobjects aggregated at the tick level are connected to construct a *mock flight schedule* that will heuristically allow or prohibit a Routeobject from being operated[6]. Based on these two issues, the feasibility of a route option is determined via a *connecting probability algorithm*.

The connecting probability, $P_c(R_{a \to b})$, measures the likelihood of a Routeobject being offered to the Consumeragent based on its feasibility. It is further postulated that the feasibility of route can be determined through two factors: flight frequency

[6]While many airspace and en-route models are designed to examine the NAS operations (delays, separations, capacity constraints, etc.) on a daily or even hourly basis, this research aims to study the NAS network behavior (topology, hubbing activities, etc.) over an extended period of time. Due to the mismatched scope and time-granularity while also to reduce the computational intensity of the solution, flight scheduling are not explicitly modeled by choice.

and route trajectory. The impact of flight frequency on route feasibility is highlighted by the fact that it is more likely to create a connecting route option when the constituting segment flights have more departing flights. Meanwhile, the impact of route trajectory on route feasibility is highlighted by the fact that route options with longer travel distance (and hence travel time) are less desirable than those with shorter distances.

A Routeobject that services any given origin and destination locales can either be a direct route or a connecting route. Examination of direct routes is simple as there is only one possible configuration, which evidently is also the configuration with the shortest possible travel distance. $P_c(R_{a \to b})$ for direct routes are then determined solely on the flight frequency of the direct segment flight. Meanwhile, there are multiple configurations possible for single-connection routes. To better understand the problem at hand, route options are abstracted into four fundamental topologies: i) hub-to-hub (R_1), ii) hub-to-spoke (R_2), iii) spoke-to-hub (R_3), and iv) spoke-to-spoke (R_4). The concept of a *zone* is abstracted as a relative separation classification between any two airports (A and B) in a connecting route via hub H. A and H are considered to be in the same zone if H is located nearer to A than it is to B. H is considered to be in a neutral zone if it is located equidistant to both A and B. The following notations are used to facilitate the discussion:

- H_{orig} : Origin hub node
- H_{dest} : Destination hub node
- S_{orig} : Origin spoked node
- S_{dest} : Destination spoked node
- H_{conn} : Connecting hub node

- Under the premise of the hub-and-spoke network system, a spoked node is said to be *a member of the H hub system* if it is served in the domain of the given hub node H.

A hub-to-hub (R_1) topology is described in reference to Figure 26. Configuration 1 shows a direct route (R_1^d), which is the most feasible option since there are typically many flights connecting hub airports. In support of this statement, the maximal clique of the baseline network model is computed to be 15, which means that the top 15 airports in the network system form a fully-connected topology or a complete graph (Refer Appendix C). A connecting route (R_1^c) will also exhibit high flight frequencies based on the same explanation above. There are two configurations in single-connection Routeobjects. HC1 is located in the neutral zone in Configuration 2. Meanwhile, Configuration 3 shows a zigzag configuration. A *zigzag* configuration is conceived as a configuration where H_{orig} and H_{dest} are nearer to one another relative to their distances to H_{conn}; emphasized by the additional distances added to the travel distance by connecting through a hub airport that is out of the shortest path trajectory. Therefore, $P_c(R_{a\to b})$ for a zigzag configuration is always lower than for other configurations unless if the constituting segment flights have significantly higher flight frequencies.

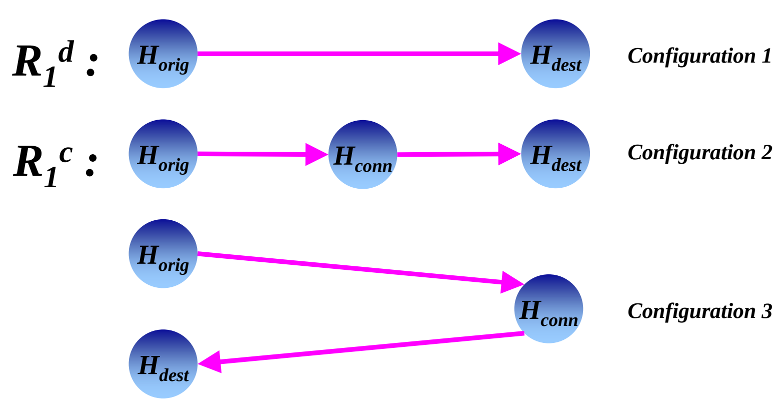


Figure 26: Configurations for Hub-to-Hub Topology, R_1

A hub-to-spoke (R_2) topology is described in reference to Figure 27. Configuration 1 shows a direct route (R_2^d). A higher flight frequency can be expected if S_{orig} is a member of the H_{dest} hub system. There are four configurations for single-connection routes (R_2^c). Configuration 2 is more feasible than the rest since it H_{dest} is a more apparent member of the H_{conn} hub system. Once again, the zigzag pattern in Configuration 5 is least feasible.

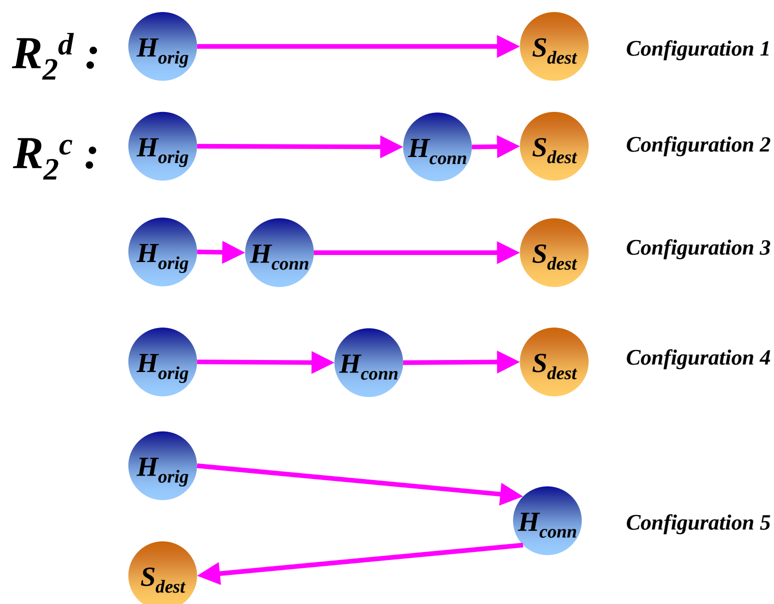


Figure 27: Configurations for Hub-to-Spoke Topology, R_2

A spoke-to-hub (R_3) topology is a mirror image of R_2 and is described in reference to Figure 28. Configuration 1 shows a direct route (R_3^d). A higher flight frequency can be expected if S_{orig} is a member of the H_{dest} hub system. There are four configurations for single-connection routes (R_3^c). Configuration 2 is more feasible than the rest since S_{orig} is a more apparent member of the H_{conn} hub system. Once again, the zigzag pattern in Configuration 5 is least feasible.

Lastly, a spoke-to-spoke (R_4) is described in reference to Figure 29. Configuration 1 shows a direct route (R_4^d); a true representation of point-to-point configuration

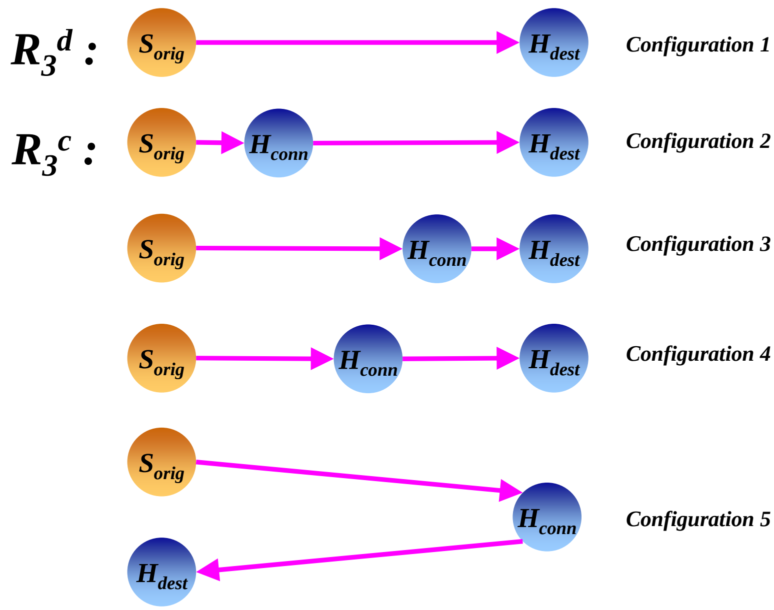


Figure 28: Configurations for Spoke-to-Hub Topology, R_3

since this segment flight serves only true O-D demand (i.e., no connecting passengers). Thus, a higher flight frequency can be expected if S_{orig} and S_{dest} is a high demand market pair. Evidently, the strong presence of low cost carriers in the NAS network has developed a large observation of such route configurations. There are four configurations for single-connection routes (R_4^c). In Configuration 2, S_{orig} and S_{dest} are both member of the H_{conn} hub system. S_{orig} and S_{dest} are members of the H_{conn} hub system in Configuration 3 and 4 respectively. These three configurations are considered equally feasible route options. Once again, the zigzag pattern in Configuration 5 is least feasible.

Having examined the four topologies for route options, the feasibility or more specifically the *connecting probability* of a Routeobject is determined based on the *shortest path method*. Based on the postulation made from examining the route topologies, flight frequency and route trajectory are selected as the weighted cost functions for this algorithm. The Dijkstra's algorithm described in Section C is used

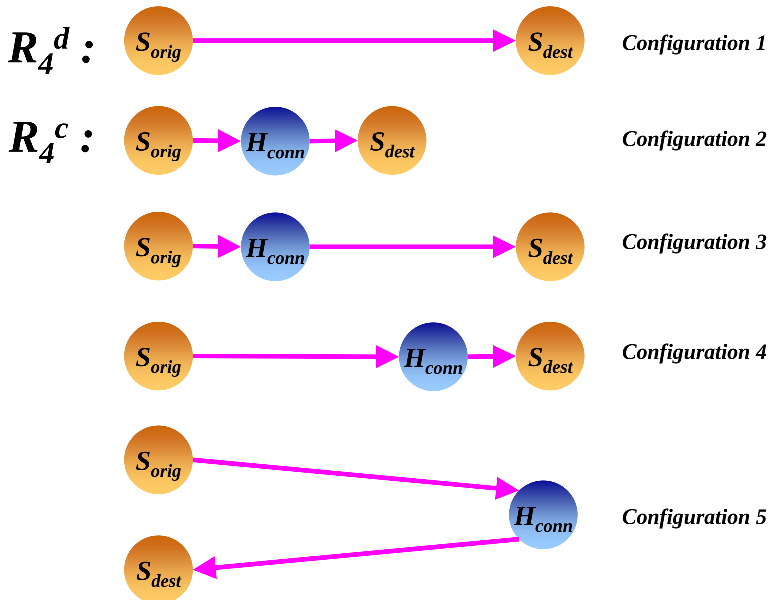


Figure 29: Configurations for Spoke-to-Spoke Topology, R_4

to solve for the shortest path.

To begin implementing the connecting probability algorithm, two independent and identical Airportobject network system is created for each Servprovagent; one for addressing the flight frequency weighted cost function (F_{freq}) and the other for addressing the route trajectory weighted cost function (F_{traj}). Since higher flight frequency indicates higher probability of creating a connecting flight (i.e. higher the better), the cost of each Segmentobject in the first network is set to one over the flight frequency. On the other hand, route trajectories with shorter distances are preferred when comparing the properties of multiple Routeobjects (i.e. lower the better). Hence, the cost of each Segmentobject in the second network is set to the segment distance. Subsequently, the values for both weighted cost functions for any given Routeobject traversing from origin a to destination b, $R_{a \to b}$, are computed and benchmarked against the shortest path, $R^\star_{a\to b}$. Depending on the .

$$P_c(R_{a\to b}|F_{freq}) = \frac{\sum_{j=1}^{k^\star} F_{freq}(S_j)}{\sum_{i=1}^{k} F_{freq}(S_i)} \tag{15}$$

$$\begin{aligned} \text{where } k = &\ \text{Number of edges traversed on } R_{a\to b} \\ \text{where } k^\star = &\ \text{Number of edges traversed on } R^\star_{a\to b} \end{aligned}$$

$$P_c(R_{a\to b}|F_{traj}) = \frac{\sum_{i=1}^{k} F_{traj}(S_i)}{\sum_{j=1}^{k^\star} F_{traj}(S_j)} \tag{16}$$

$$\begin{aligned} \text{where } k = &\ \text{Number of edges traversed on } R_{a\to b} \\ \text{where } k^\star = &\ \text{Number of edges traversed on } R^\star_{a\to b} \end{aligned}$$

Since the two weighted cost functions are independent functions, the joint probability of these two weighted cost ratios are computed as the product of the two probabilities. This joint probability is coined the *connecting probability* and is expressed as:

$$P_c(R_{a\to b}|F_{freq}, F_{traj}) = \frac{\sum_{j=1}^{k^\star} F_{freq}(S_j)}{\sum_{i=1}^{k} F_{freq}(S_i)} \cdot \frac{\sum_{i=1}^{k} F_{traj}(S_i)}{\sum_{j=1}^{k^\star} F_{traj}(S_j)} \tag{17}$$

$$\begin{aligned} \text{where } k = &\ \text{Number of edges traversed on } R_{a\to b} \\ \text{where } k^\star = &\ \text{Number of edges traversed on } R^\star_{a\to b} \end{aligned}$$

A binary probabilistic selection process is developed using $P_c(R_{a\to b}|F_{freq}, F_{traj})$ as the probability of offering a feasible Routeobject for servicing a given Tripobject demand. Evidently, the condition that seats are available on all constituting Segmentobjects for the given Routeobject must first be satisfied. Therefore, $P_c(R_{a\to b}|F_{freq}, F_{traj})$ becomes the overall selection criteria that addresses all the issues pertaining the nature of modeling aggregated segment operations without having an explicit schedule.

The flight frequency cost function addresses the higher likelihood for route options to connect through hub airports since flight segments attached to hub airports typically have high frequencies. The route trajectory cost function addresses the lower likelihood of Servprovagents offering zigzag connections since these connecting routes incur significantly longer distances, therefore reducing the attractiveness of the route option. However, for short distance Routeobjects in the vicinity of locales with primary large hubs such as Los Angeles, New York, and Atlanta, the effects of the route trajectory cost function may be overshadowed by the effects of the flight frequency cost function. This leads to connecting probabilities that may be higher than expected, for instance, i) routes servicing San Diego to Los Angeles connecting through San Francisco and ii) routes servicing Tampa to Jacksonville through Atlanta. In addition, since this algorithm is imposed for individual carrier's network system, carriers with a limited network system may only have zigzag configurations for servicing a specific O-D pair, which happens to also be the shortest path option. This would then give this unattractive route option a connecting probability of one. However, such route options would incur significant travel time and connection time, which are eventually captured by the Consumeragent mode choice selection model.

Network adaptation model

An inventory control meta-model is formulated to facilitate the network assessment and perturbation processes within the network adaptation model. The key concept behind the meta-model is the effective seat capacity, which takes into consideration the perishable nature of aircraft seats. The effective seat capacity is defined as the total number of seats on an aggregated Segmentobject that can be effectively sold to Consumeragents for the given tick, given the fact that individual flight segments that constitute the Segmentobject departs at various load factors. Previous average load factors are used to compute the effective seat capacity. The initial run (tick = 1) uses average load factors for the flight segments are reported by the T-100 operations data. For the simulation runs with tick 2 and up, average load factors from the previous two ticks are used not only to update the effective seat capacity but also to perturb flight frequency if needed based on the following algorithm:

<u>Initialization</u>

Expected load factor at tick $t = 1$, $E(LF_{t=1}) = \max(LF_{min}, \frac{\text{Total passengers reported}}{\text{Total seats reported}})$

Expected load factor at tick $t = 2$, $E(LF_{t=2}) = \max(LF_{min}, LF_{t-1})$

Expected load factor at tick $t > 2$, $E(LF_{t>2}) = \max(LF_{min}, LF_{t-1}, LF_{t-2})$

<u>Adaptation</u>

If $\frac{LF_{t-1}}{LF_{t-2}} > \omega$

  Set $E(LF_t) = \min(LF_{max}, \max(LF_{t-1}, LF_{t-2}) + \alpha)$

If $E(LF_t) > LF_{crit}^{high}$

  $freq = freq + 1$

If $(LF_{t-1} < LF_{crit}^{low})$ & $(LF_{t-2} < LF_{crit}^{low})$ & $(freq \neq 0)$

  $freq = freq - 1$

<u>Parameters:</u>

LF_k = Load factor at the end of the k^{th} tick

LF_{min} = Minimum allowable load factor

LF_{max} = Maximum allowable load factor

LF_{crit}^{low} = Critical load factor for decrementing flight frequency

LF_{crit}^{high} = Critical load factor for incrementing flight frequency

ω = Critical ratio for updating load factor

$freq$ = Flight frequency

α = Updating step size

While the implemented algorithm remained a reactive one, real airlines are not known to actively taking predictive (hence financially risky) measures against changing demand. Therefore, the network adaptation model adequately served the purpose of adapting seat inventory level and addressing the evolution of the network configuration and density of these service networks much like how real airlines would. It is also noted that airlines do not make short term capacity changes at high frequencies. Thus, this network adaptation model is only active once every few ticks. The capacity limit specified for each airport remained enforced to ensure that the network system was constrained to the 2004 capacity benchmark levels. If desired, this limit could be relaxed or even released to reflect unconstrained scenarios depending on the scope of the investigations.

4.3.2.4 Pricing Subagent

Overview

The pricing subagent addresses both the pricing and revenue management core functions by implementing a dynamic pricing algorithm. Dynamic pricing differs from the conventional Revenue Management System (RMS) in the sense that the flight fare is not known to the service provider at the trip request arrival, which is oftentimes the case in reality. The pricing core function determines the base fare with respect to the cost structure of a Segmentobject. The pricing subagent then introduces dynamic pricing adjustments to the base fare emphasizing on the advance purchase period of the trip request, which is one of the most significant market segmentation factors considered by airlines. A *perceived demand function* is the backbone behind this dynamic pricing model along with a experiential learning method.

Base fare determination

The base fare for a trip request is calculated as a marked up fare of the estimated TOC of serving one passenger on the given Routeobject. This calculation begins with the computation of an expected TOC per passenger on a segment flight, s_i ($ETOC^{s_i}_{pax}$) for all the Segmentobjects that constituted the Routeobject, $\overline{S^R}$. The resulting value of $ETOC^{s_i}_{pax}$ is an *expected* estimate since the DOC and IOC_a cost components must be divided by the actual number of revenue passengers for each

Segmentobject, which is not known until the end of the simulation run. Therefore, the pricing subagent use an expected revenue passenger count for this computation. Similar to the aforementioned inventory control meta-model, the average load factor from the previous simulation run is used to compute the expected revenue passenger count ($EPAX$). Equation (13) then becomes Equation (18) to calculate $ETOC^{s_i}_{pax}$.

$$\begin{aligned} ETOC^{s_i}_{pax} =& \frac{TOC_{flight}}{EPAX} \\ =& (\frac{DOC}{hour})(\frac{T_{flight}}{EPAX}) + \frac{IOC_a}{EPAX} + IOC_b \end{aligned} \tag{18}$$

$$\begin{aligned} \text{where } T_{flight} =& \text{Total flight time} \\ EPAX =& \text{Expected revenue passenger count} \end{aligned}$$

Evidently, $ETOC^{s_i}_{pax}$ decreases with a higher value of expected load factor as shown in Figure 30. Thus, the approach of feed-forwarding previous average load factors not only allow Servprovagents to price more competitively, it also has an indirect influence on distinguishing between fares for direct and single-connection route options. This is performed based on the fundamental understanding that segment flights between hub airports tend to exploit economies of scale such that higher operating load factors can be achieved. Fares for connecting Routeobjects are thus, anticipated to reflect this higher operating load factor which then translates to lower base fares.

The estimated TOC for the entire Routeobject, TOC^{R}_{pax}, is then computed as the sum of $ETOC^{s_i}_{pax}$ for $s_i \in \overline{S^R}$.

$$TOC^{R}_{pax} = \sum_{i=1}^{K} ETOC^{s_i}_{pax} \tag{19}$$

$$\text{where } K = \text{Number of constituting segment flights}$$

The base fare, $FARE^{R}_{base}$ is obtained by taking a marked up value of TOC^{R}_{pax}. Depending on whether R is a direct or connecting Routeobject, a premium or discount multiplier is further imposed.

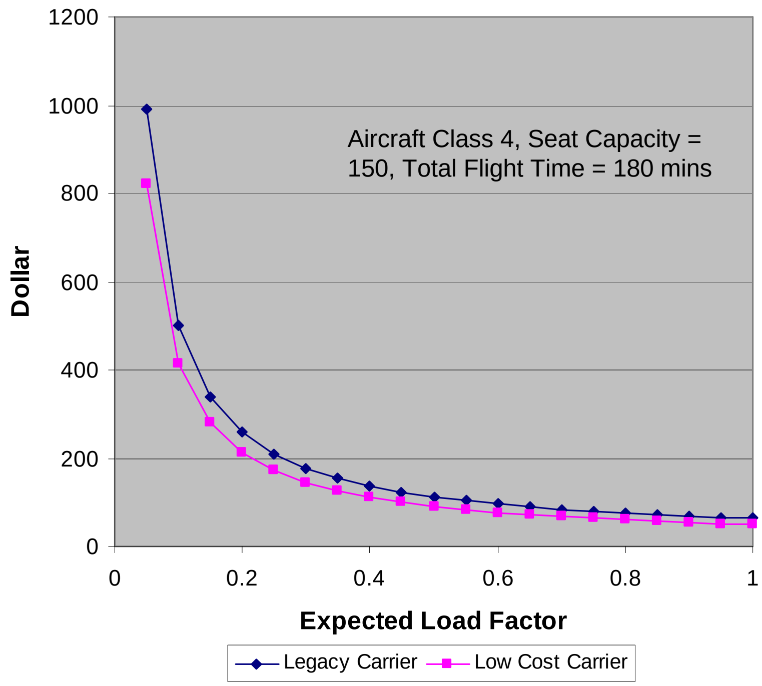


Figure 30: Total Operating Cost vs. Expected Load Factor

$$FARE^R_{base} = \begin{cases} TOC^R_{pax} \times (1 + \pi_{markup}) \times (1 + \pi_{direct}) & \text{if } R \text{ is direct} \\ TOC^R_{pax} \times (1 + \pi_{markup}) \times (1 - \pi_{connecting}) & \text{if } R \text{ is connecting} \end{cases} \tag{20}$$

$$\text{where } \pi_{direct} \;\&\; \pi_{connecting} > 0$$

Perceived demand function

It has became a commonly accepted knowledge and industry practice that fares typically increase as the travel time draws closer and the number of remaining seats declines. Real world airlines use market and operations data gathered over decades of operations to decipher and inherently to exploit this consumers' purchasing behavior. Lacking this data, the dynamic pricing model addressed the advance purchase pattern through a *perceived demand function*. This function is uniquely defined for each Servprovagent as the premise for estimating the consumers' willingness to buy as perceived by service providers, or simply put, the probability of a consumer paying \$$P$ from a specific fare class, δ (out of i fare buckets) for a seat purchased from a specific advance purchase period, α (out of j advance purchase periods). The probability values for different combinations of advance purchase period and fare buckets, $p_{\alpha,\delta}$ are recorded in a matrix format as shown in Figure 31. The manner in which the perceived demand function is used for adjusting fares is described next.

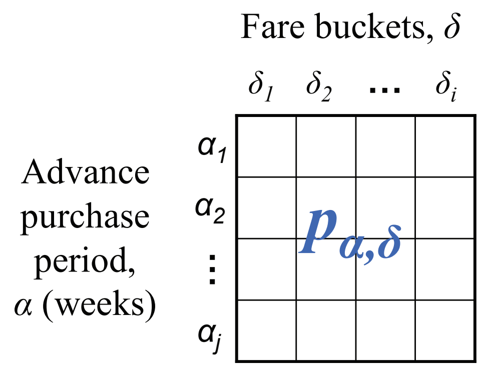


Figure 31: Perceived Demand Function for Advance Purchase Dynamic Pricing

Experiential learning method

The perceived demand function merely facilitates price adjustments based on the advance purchase period. To improve this price adjustment, the dynamic pricing model employed an experiential learning method. *Experiential learning* is a general term coined to describe the process of learning from direct experience. The learning method implemented for the pricing subagent used feedbacks from previous simulations in the forms of average load factors and mode choice selection outcome to incrementally reevaluate the decision-making mechanism of this deliberate subagent entity. The experiential learning method is derived based on the *underlying concepts* of the Reinforcement Learning (RL) technique (See Appendix E for details). The stochastic nature of the TransNet model led to a consistently stochastic approach when developing this learning method. The discussion for this method begins with the RL adaptation for the pricing research problem.

The four elements of RL are policy, reward function, value function, and model. Via the subagent concept, the goals of fare adjustments can be altered to be aligned with or different than the main service provider agent's goals. Due to the overwhelming presence of revenue management in the airline industry, the familiar goal of pricing is thus, to maximize total revenues. Therefore, the policy for fare adjustments is to choose the fare class that maximizes the expected returns from selling a seat under a ε-greedy method. A greedy method will ensure that the action that returns the highest immediate reward is selected always (exploitation approach). An ε-greedy method allows for a probability of selecting other action options in an exploration approach. An ε value of 0.3 is prescribed for this method.

The reward function is built into the stochastic model and retrieves the immediate reward for selecting an action using the aforementioned policy based on Equation (21).

$$R = \begin{cases} 0 & \text{if seat is not sold} \\ FARE^R & \text{if seat is sold} \end{cases} \tag{21}$$

The value function is represented by the perceived demand function, which is constantly reevaluated throughout the simulation such that the subagent continues to make desirable fare adjustments in the long run. The reevaluation of the value function is performed by providing feedbacks from the previous states through an *incremental implementation*. Sutton and Barto (1998) described incremental implementation as devising "incremental update formulas for computing averages with small, constant computation required to process each new reward". Compared to other action-value methods which have higher computational and memory requirements for computing averages of past rewards for the reevaluation process, this method requires memory only for the old estimate and the step size, which can be generalized as:

$$\text{New estimate } \leftarrow \text{Old estimate} + \text{Step size} \times (\text{Target - Old estimate}) \tag{22}$$

where the (Target - Old estimate) term refers to the error of the estimate. The general idea of the implementation for TransNet is to increase the probability of selling at the next higher fare class if previous batches of trip offers made were successfully sold and vice versa, to increase the probability of selling at the next lower fare class if previous batches of trip offers were rejected. The error term in Equation (22) is represented as a unit count every time a published offer is accepted or rejected by the Consumeragent. After this unit count reaches a target value (batch), a new estimate that reevaluates the perceived demand matrix is prescribed based on a given step size, ξ. The algorithm for this implementation is as follows:

If offer made in fare class F_k is accepted

    Increase $p_{\alpha,\delta}$ in F_{k+1} by ξ

    Decrease $p_{\alpha,\delta}$ in F_{k-1} by ξ

If offer made in fare class F_k is rejected

    Increase $p_{\alpha,\delta}$ in F_{k-1} by ξ

    Decrease $p_{\alpha,\delta}$ in F_{k+1} by ξ

Order of fare classes: $F_{k+1} > F_k > F_{k-1}$

The step size, ξ, also known as the learning rate, is kept as a small positive value to reduce the error caused by asynchronous updating. The value of ξ is allowed to decay over the number of iterations through many different expressions. Gosavi (2003) recommended multiple ways of updating step size, one of which is to simply divide the step size by the number of iterations, n. This is also where the experience from previous runs come into play in the learning process, hence, experiential learning. Lastly, the model for which immediate rewards and feedbacks are retrieved from in the learning method is the integrative demand-supply model. Transportation activities that are generated through the simulation fuels the stochastic approximation of this learning method.

Applying the learning method to the problem, the dynamic pricing subagent has a long term goal of maximizing the total revenues with a ε-greedy policy. In a non-competitive marketplace with excess demand, the strategy is simply to price each seat at the highest possible fare without forcing trip cancelations. However, in a competitive environment where other service providers and ground transportation modes may be competing for the same trip demand, the dynamic pricing subagent has to learn to modify the probability values ($p_{\alpha,\delta}$) of the perceived demand function such that the long term goal can be achieved. This may result in a solution where the price offered for a given trip request is not the highest attainable price but instead the method seek for the maximum total revenues at the end of the simulation run.

4.3.3 Transportation Activities Simulation

As mentioned earlier, transportation activities are the outcome of the integrative demand-supply model. The actual process flow of a consumer trip demand transaction is illustrated in Figure 32.

First, Consumeragents and their corresponding wishlist Tripobjects demand are generated based on the agents' attributes in each locale. Destination locales for these Tripobjects are determined from the hypothetical gravity-based trip distribution model. At this point, a Tripobject demand with known origin locale, destination locale, batch size, and advanced purchase period is obtained. The coupling of these two stakeholders began with the Consumeragent making simultaneous trip requests

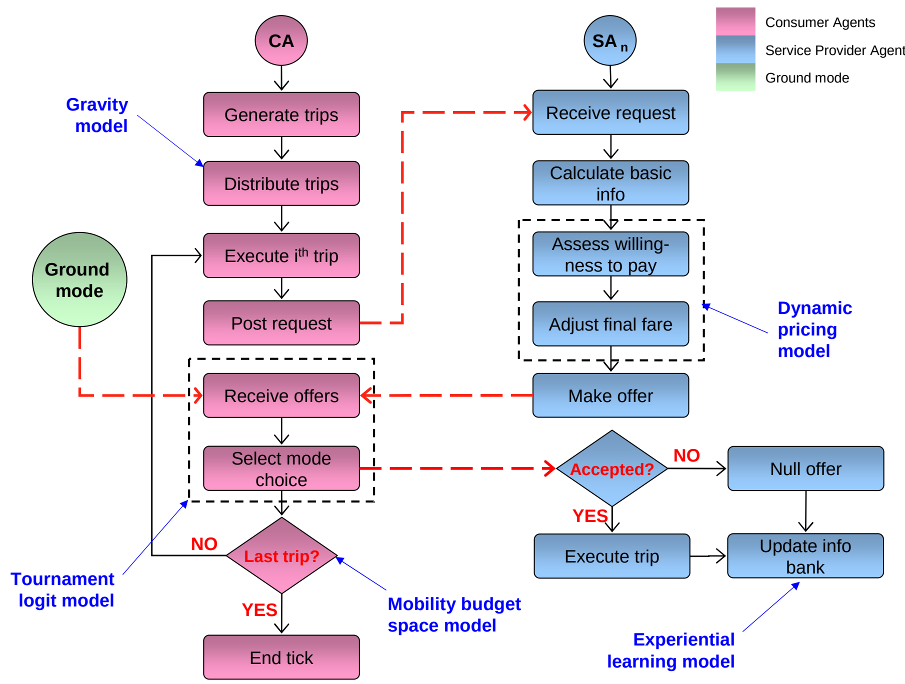


Figure 32: Integrative Demand-Supply Modeling Flow Process

to multiple Servprovagents. Upon receiving the request, the basic fare and time information for the given request are calculated by each Servprovagent. The pricing subagent for the Servprovagent is then activated, where a dynamic pricing method is used to adjust the basic fare based on Consumeragent's perceived willingness to pay judged by the advanced purchase period of the request. Under this method, each Servprovagent possessed a unique demand function, which specified the probability of purchase for any given combination of fare class and advanced purchase period pair. The combination pair with the highest expected value is selected via an ε-greedy algorithm. A final fare offer is then made to the Consumeragent, who in turn compares the cost and time information with those obtained from other competing Servprovagents and ground transportation mode. The eventual mode choice is selected via the Tournament Logit Model and all competing Servprovagents discover whether or not their offer was accepted. Specific details of the selection such as winning mode and final fare are withheld to maintain a level of in-transparency between Servprovagents. Based on this mode selection outcome, the perceived demand function within the information bank of each Servprovagent is updated to reflect the success or failure of each transaction.

The methodology described above is intended to illustrate how a Consumer-agent's mode selection process is tightly coupled with the pricing mechanism of each Servprovagent at the microscopic level. Vice versa, the adjustments made to the Servprovagents' information banks after each transaction is intended to reflect the market feedback onto the service provider business models via the pricing sub-agent (continuous or short-term response) and routing subagent (long-term response). When aggregated, these tightly-coupled interactions give rise to the complex and adaptive interrelationship that initiates the market dynamics in the aviation SoS.

CHAPTER V

MODEL VERIFICATION & VALIDATION

5.1 Overview

Verification and validation are two of the most important and challenging tasks in a modeling and simulation exercise. Model verification entails the ongoing process of assuring the veracity of both the individual and overall model implementations when compared against the conceptual specifications envisioned by the developer in performing a given set of tasks. This process is critical in the modeling and simulation exercise because it ensures the accurate translation of conceptual ideas into mathematical and/or methodological representations. Meanwhile, model validation entails the process of determining how accurately the model can represent the real world within the confined scope and perspective of the model environment.

Lewe (2005) provided an informative pictorial summary of an expanded modeling and simulation paradigm based on literature from (Sargent, 2000), as depicted in Figure 33. From this paradigm, a *weak validation*, in which most modeling and simulation activity are based upon, is achieved when the 'computerized model becomes logically equivalent to the proxy world with compromised cost and confidence." Meanwhile, a *strong validation* is achieved when the weak validation model is shown to be equivalent to the real world. Key issues and debates regarding the validation

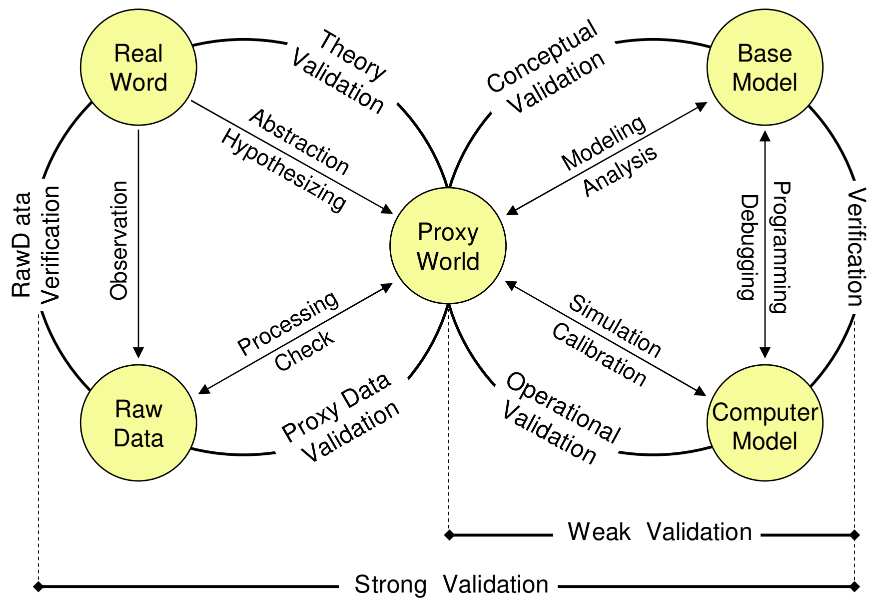


Figure 33: Simple Modeling and Simulation Paradigm (Source: Lewe (2005, p.113))

of agent-based models are discussed, with the gist of the discussion being that while strong validation of agent-based models is a tremendous challenge, verification and weak validation must be provided for the models. Lewe proceeded to offer several principles for validating the design on an agent-based model:

1. Keep the underlying construct of the model simple
2. Seek weak validation for the model
3. Refrain from using the same data sets for both model construction and validation
4. Use sensitivity analysis to identify fundamental behaviors of the model

5.2 Base Model Calibration

Even though the conceptualization of the demand and supply models were concurrently formulated, each of the models was designed to run independently from one another. However, since integration of the demand and supply components is the thrust of this research, the independent simulation using of any one model will require a meta-presence of the other model; in the form of a database input or a simplified meta-model. Since calibration data for demand and supply are also available separately, the demand and supply models of TransNet were calibrated independently before adjoining them for a collaborative simulation. Within each model's calibration are also multiple phases of calibrating efforts that are designed to yield the most accurately represented model of the NTS while remaining computationally viable. These efforts are discussed in the next sections.

5.2.1 Demand Model

The demand model is calibrated in three sequential phases. Phase I emphasized the calibration of Consumeragent and Tripobject definitions such that the resulting travel profile matches the actual travel behavior observed in the CONUS. The 1995 ATS is the best available *proxy-world* representation of the travel behavior in the CONUS and is used as the calibration data source. The outcome of this calibration phase is a well-defined set of demand parameters that yields an accurate representation of the transportation mode selection process. Using the parameters setting from Phase I, Phase II emphasized the calibration of the gravity-based trip distribution model, which improves the overall fidelity of the methodology by distributing consumer trips via a hypothetical algorithm that is independent of the 1995 ATS data source. Phase III emphasized the calibration of the true aviation O-D demand generation against the baseline $\tau_{ij,av}$ extracted from the sDB1B database.

The three calibration phases are thoroughly discussed next. The successful calibration of the demand model in its entirety is regarded as one of the key contributions of this research since there is now a tool for forecasting aviation demand strictly based on the fundamental properties of consumers and their geographic locations without having to rely on loosely estimated terminal area growth factors.

5.2.1.1 Phase I: Mode Selection Calibration

Since the scope of this demand research is derived from the multimodal transportation relationships rather than generating aviation demand from historical aviation data, the travel mode selection process of traveling consumers is the focal point of the analysis in Phase I calibration. The objective for the calibration is to obtain NAS level modal split ratio as a function of trip distance without dwelling into individual trip outcomes. Due to the largely different trip characteristics between business and personal (also known as leisure) trips, the demand model is calibrated for enterprise Consumeragents and household Consumeragents individually. Therefore, household trips modal split data for different trip distance groups were extracted from the 1995 ATS for business and personal trip purposes. The polynomial-based pricing function shown in Equation 10 was used as a simplified treatment of the air fare pricing.

The probability values for the overnight stay function of long distance ground trips that best capture the modal split behavior are $p_1 = 0.8$, $p_2 = 0.5$, $p_3 = 0.45$, and $p_4 = 0.4$ (See Equation 8). p_1 is set at a much higher value than the other probability values to reflect the initial psychological leap when an overnight stay penalty of ground transportation modes first appear unfavorable and/or indifferent to air transportation modes due to the long driving time and effort required. The hotel room rate is assumed to be \$50 per night and the additional overnight stay time is probabilistically sampled from a triangular distribution $\triangle\{6, 8, 10 \text{ hours}\}$.

When the modal split ratio is aggregated for different trip distance groups, it is postulated that the effects of competition and supply constraints are masked by the much more dominant trip time and trip cost factors, which are sufficiently captured by the simplified pricing function and the mode selection model within each Consumeragent. With that postulation, an arbitrarily large number of trips were generated and distributed using the methods implemented in the TransNet demand model. Trip time and cost information using both ground and air transportation modes were computed for each trip demand, where the eventual mode choice was determined via the tournament logit mode selection model. The final value for the calibration constant, α, in Equation 12 was 0.018. Finally, the resulting modal split ratio was compared against the observed data from the 1995 ATS. This overall process for Demand Calibration Phase 1 is illustrated in Figure 34.

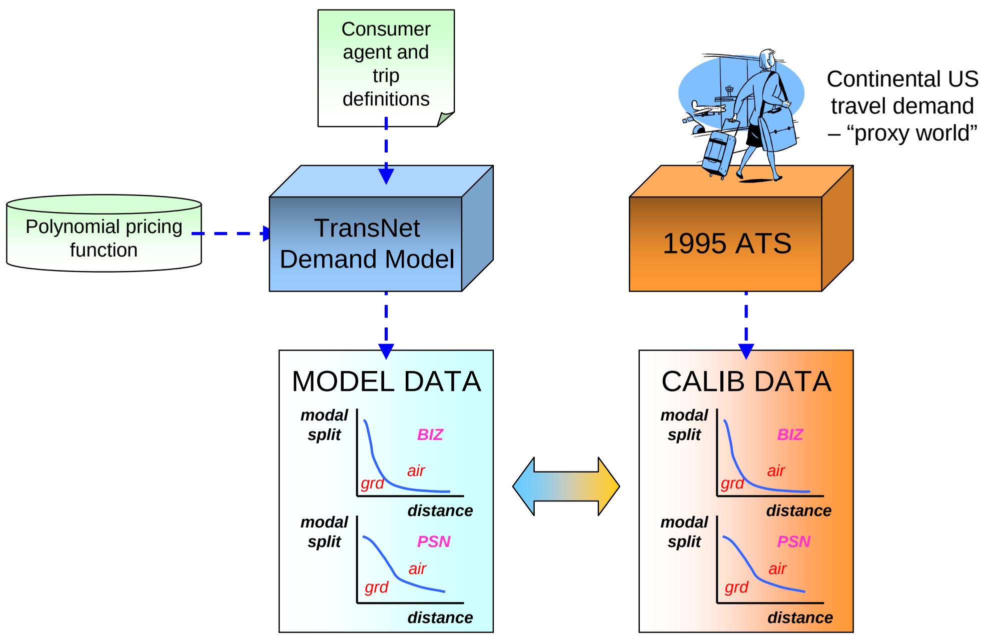


Figure 34: Demand Calibration Phase I: Mode Selection Calibration

Two primary comparisons with respect to trip distance were made when performing the Demand Calibration Phase I: i)Modal split ratio between air and ground modes and ii)normalized total trip counts. Figure 35 to Figure 37 show that the predicted modal split ratio for business, personal, and all trip purposes are well-matched against the 1995 ATS observed data. This result provided great confidence in the fundamental construct of the Consumeragents and Tripobjects particularly in the mode selection model.

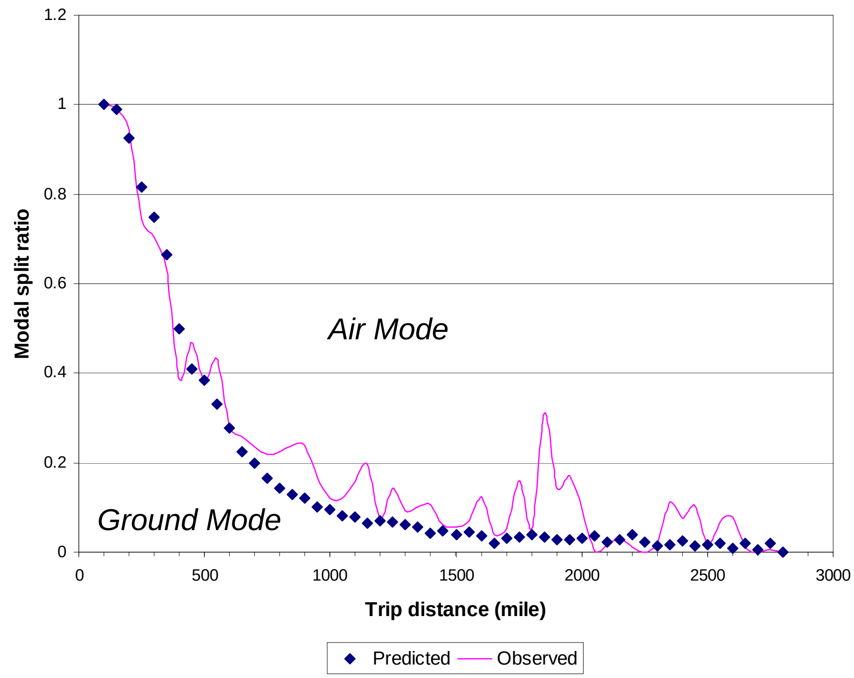


Figure 35: Demand Calibration Phase I: Business Trips Modal Split Ratio

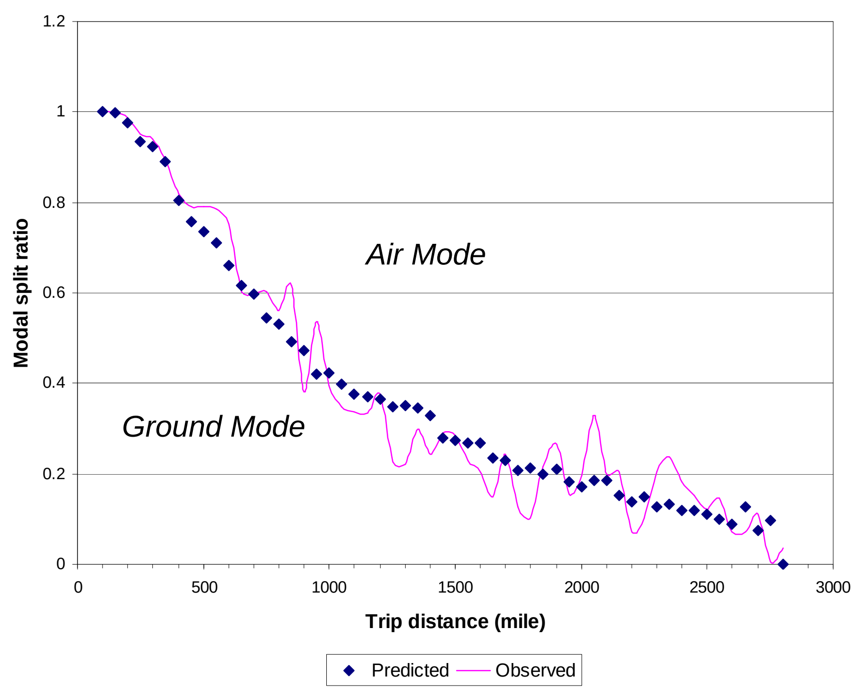


Figure 36: Demand Calibration Phase I: Personal Trips Modal Split Ratio

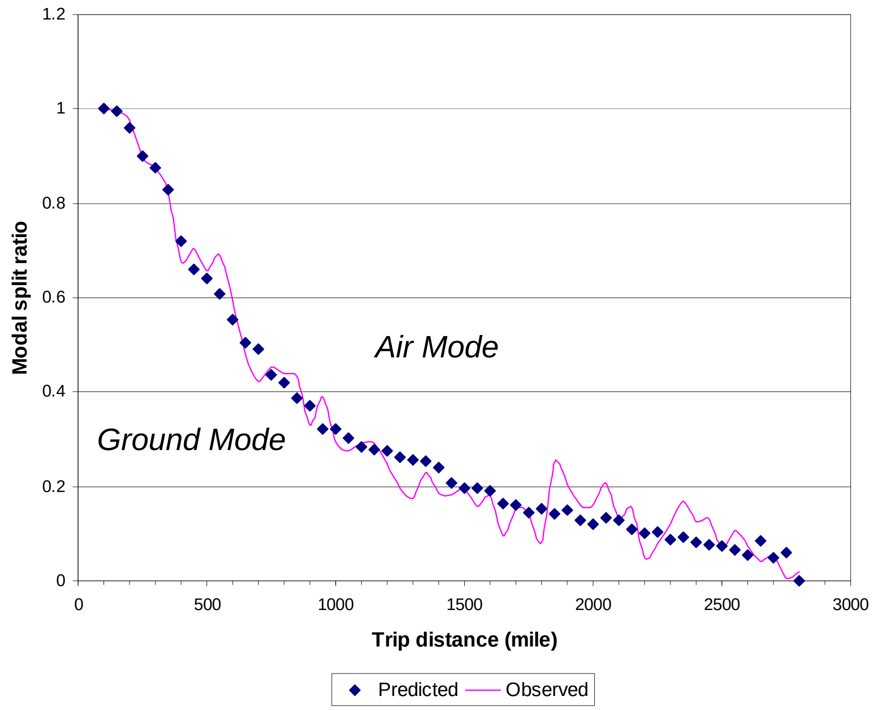


Figure 37: Demand Calibration Phase I: All Trips Modal Split Ratio

Figure 38 to Figure 40 show that the predicted normalized total trip counts for business, personal, and all trip purposes are also well-matched against the 1995 ATS observed data. A logarithmic scale is used for the normalized total trip counts plot to highlight the data comparisons especially at trip distances of less than 1000 miles where two thirds of the total trips occur. This result implied the validity of the proportionate magnitude between the ground and air modes and further reinforced the validity of the demand model particularly in terms of the trip generation process.

5.2.1.2 Phase II: Trip Distribution Calibration

By now, the demand model has a well-calibrated mode selection process. As discussed in Section 4.3.1, the two main reasons for distributing trips via a hypothetical model is to refrain from being overly reliant on the 1995 ATS data source for model construction since it is also the calibration data source and that there exists significant errors

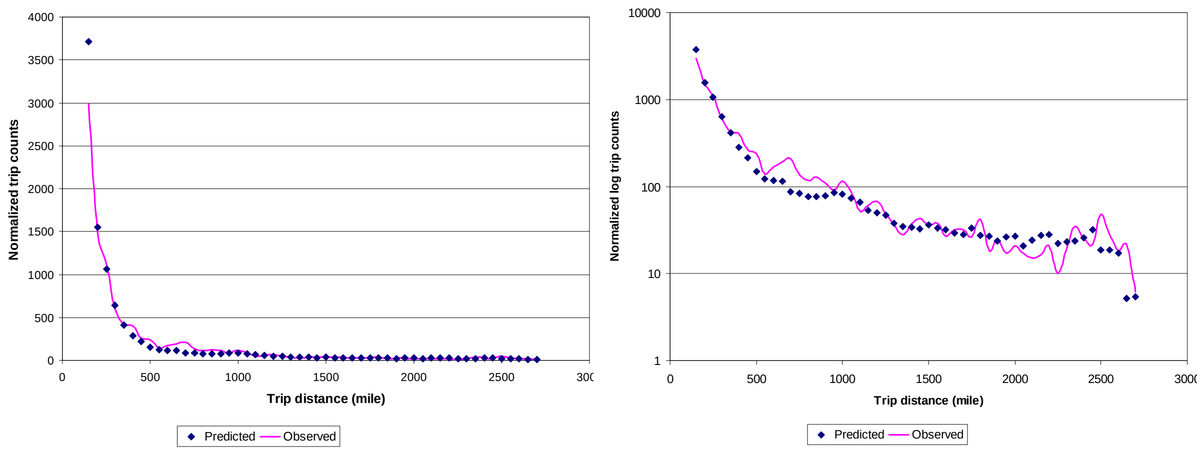


Figure 38: Demand Calibration Phase I: Business Trips Normalized Total Trip Counts

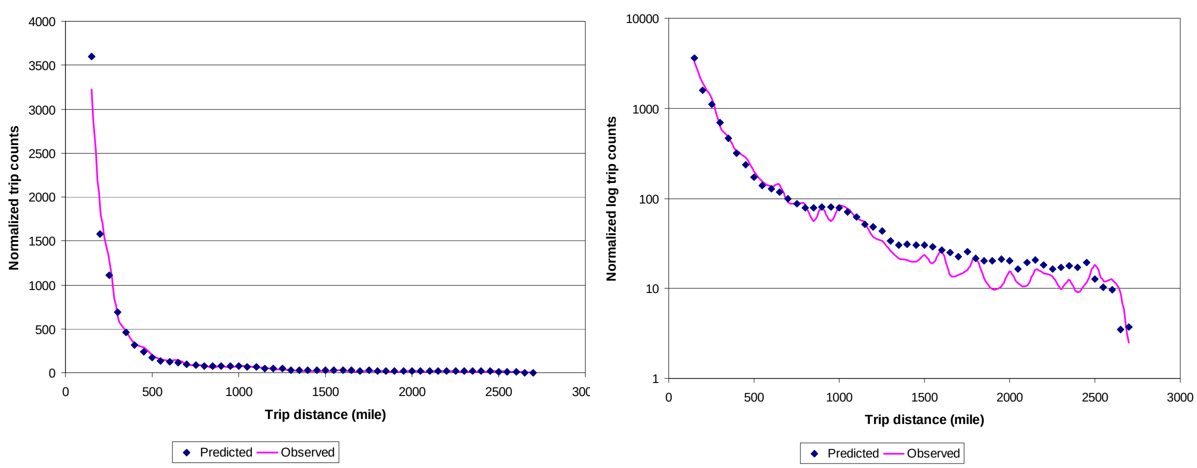


Figure 39: Demand Calibration Phase I: Personal Trips Normalized Total Trip Counts

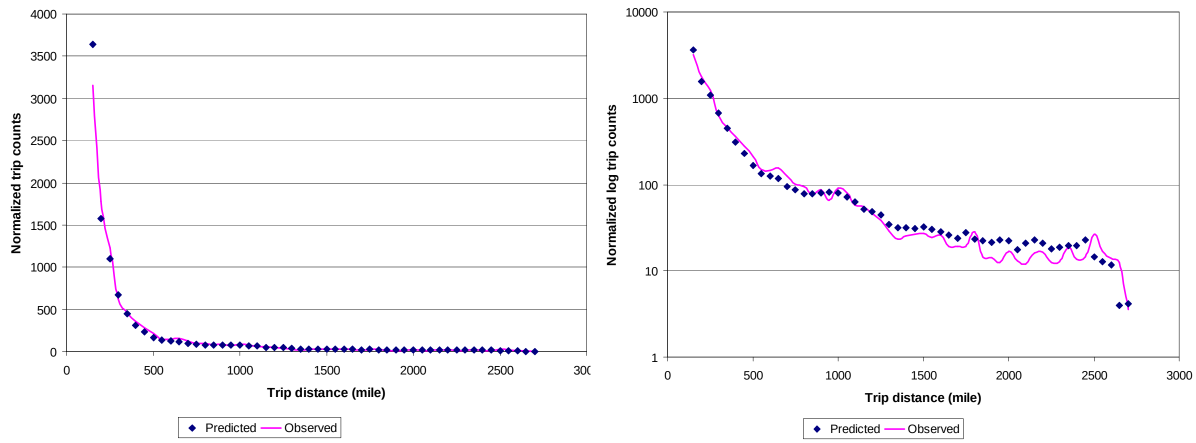


Figure 40: Demand Calibration Phase I: All Trips Normalized Total Trip Counts

and data anomalies in the database when used at the O-D level. Subsequently, the Demand Calibration Phase II was conceived to validate the hypothesized distribution model against 1995 ATS true O-D demand data set (π_{ij}). An aggregated method for comparing large distribution sets formulated by Yang et al. (2008) called the L-strip method was used. This method reduces a two-dimensional *ranked* data set into a one-dimensional data set by summing the horizontal and vertical strips (L-strips) of a row position and using that L-strip sum as the means of comparison. Depending on the nature of the data, the ranking order is determined by the user. Two forms of comparison are prescribed; the first compares the cumulative distribution function (CDF) of the L-strip sums and the other compares predicted results against the previously determined ranking parameter.

In the case of true O-D demand, the π_{ij} matrix was ranked in the order of the sum of produced and attracted trips of each locale, which is equivalent to the sum of transportation activities for the locale. The same procedures were performed to the true O-D demand matrix predicted by the demand model simulation that used β and γ values obtained in Section 4.3.1.4. The L-strip sum CDF generated from the model run were shown to match well against the observed L-strip sum CDF from the π_{ij}

matrix as depicted in Figure 41. This indicates that the hypothetical gravity-based distribution model was able to accurately capture the true O-D demand distribution. A logarithmic scale plot was used for comparing the sum of attracted and produced trips between the top ranked locales. Figure 42 shows a close proximity between the predicted and the observed data, which further reinforced the validity of the demand model particularly in terms of the trip distribution process.

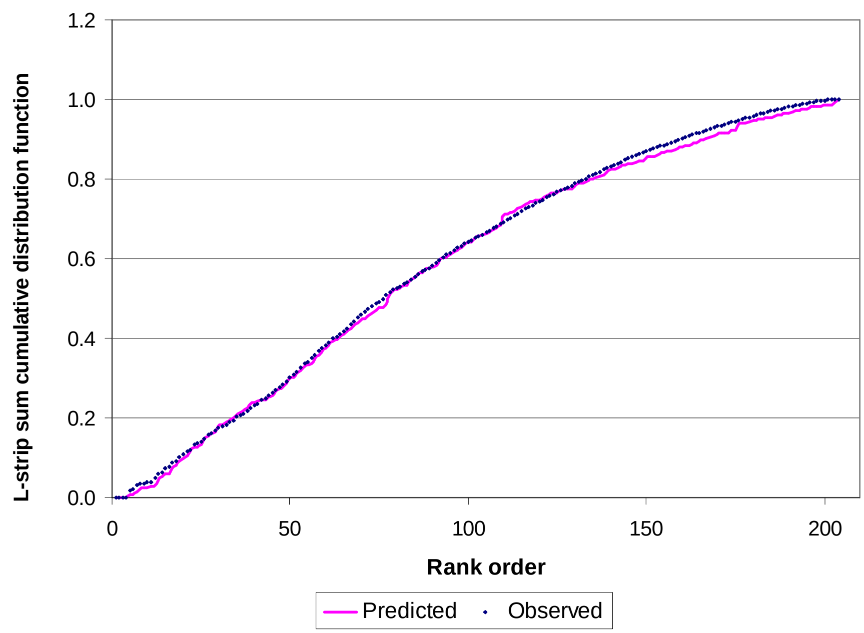


Figure 41: Demand Calibration Phase II: Cumulative Distribution Function for Total Trips

5.2.1.3 Phase III: Aviation Demand Calibration

The Demand Calibration Phase III is the first step towards validating the demand model against an aviation demand data source, namely, $\tau_{ij,av}$ from the sDB1B database. This phase is procedurally identical to the Demand Calibration Phase II in that the hypothetical trip distribution model was used to generate trip demand and the L-strip sum method is used for making comparisons. However, only the aviation demand was

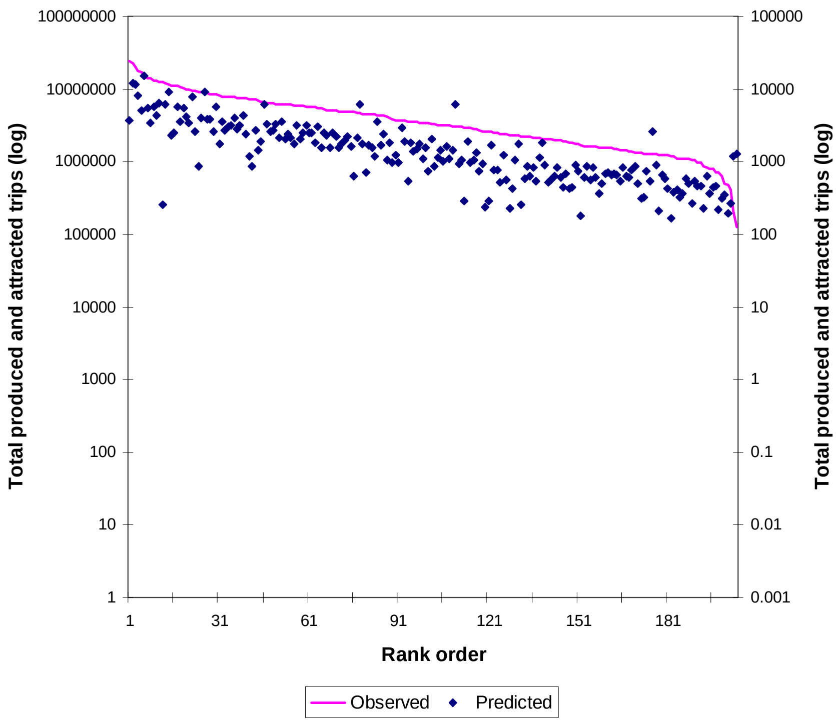


Figure 42: Demand Calibration Phase II: Total Produced and Attracted Trips (log scale)

extracted from the total trip demand and compared against $\tau_{ij,av}$. Nonetheless, it has been duly noted that while the model predicts true aviation demand, $\tau_{ij,av}$ actually represents airport-based O-D demand that may include reconnected demand originating from nearby locales with poorly accessible commercial air services (see Section 4.2.3) .

In the case of true aviation O-D demand, the $\tau_{ij,av}$ matrix was also ranked in the order of the sum of produced and attracted trips of each locale. The same procedures were performed to the true aviation O-D demand matrix predicted by the demand model. Before proceeding with the calibration, both the predicted and observed aviation data were scaled to a daily NAS operation level under normalcy conditions such that a coherent comparison between the two data sets in terms of aviation demand volume can be obtained. The outcome of this comparison shows that the predicted L-strip sum CDF matched well against the observed L-strip sum CDF. This indicates that the mode selection and hypothetical gravity-based distribution models were able to accurately capture the true aviation O-D demand distribution. In addition, Figure 44 shows a close proximity between the predicted and the observed data for the total produced and attracted trips.

These reported results served as strong evidences in testifying the first part of **Hypothesis 4**, in that the true aviation O-D demand generated by the demand model can be successfully calibrated and validated to match the $\tau_{ij,av}$ data set.

5.2.2 Supply Model

The supply model is calibrated in two sequential phases. Phase I emphasized the functionalities and adaptive mechanism of the pricing and routing subagents under a static simulation environment. Phase II emphasized the baseline network model by capturing the benchmark aviation demand from the sDB1B database while concurrently

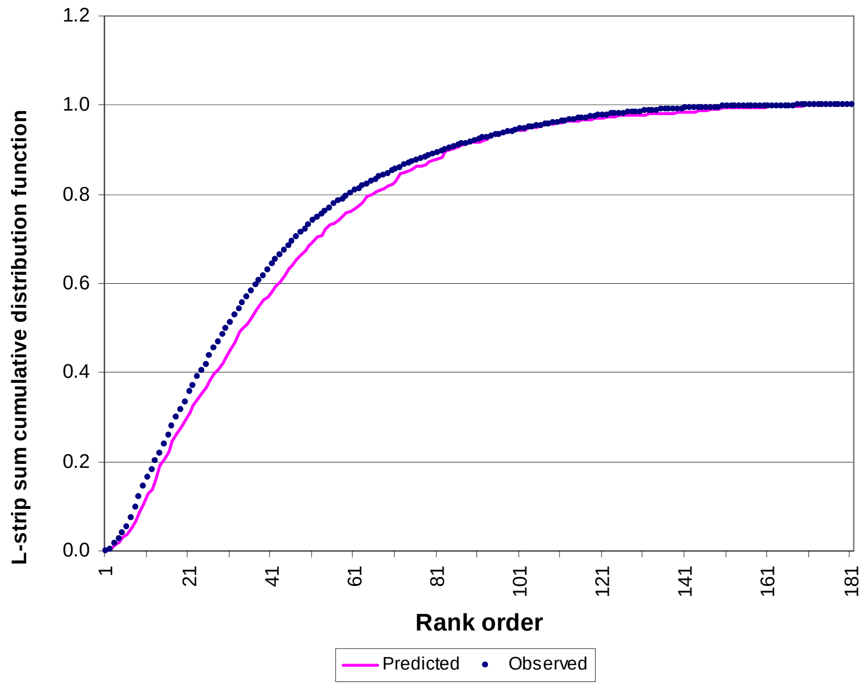


Figure 43: Demand Calibration Phase III: Cumulative Distribution Function for Total Passengers

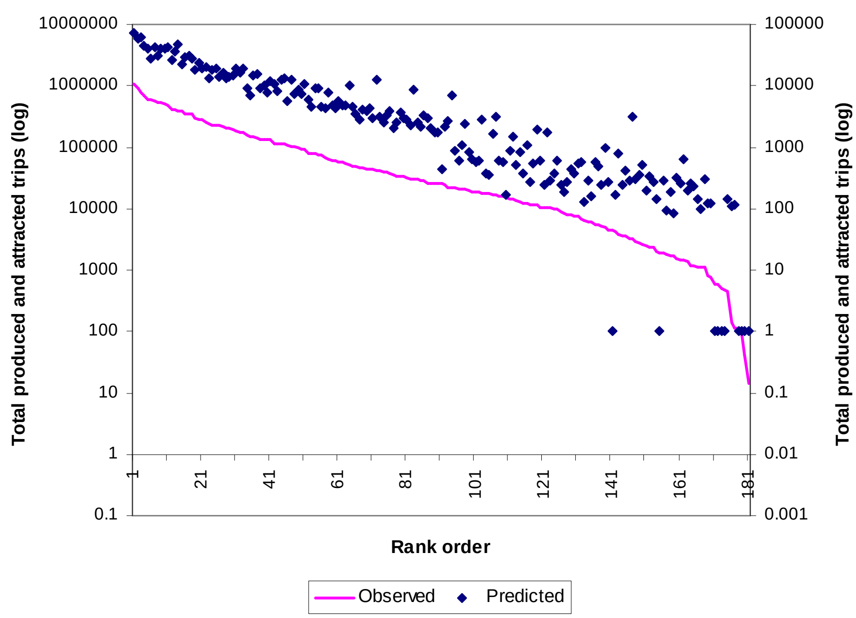


Figure 44: Demand Calibration Phase III: Total Produced and Attracted Trips

matching the benchmark enplanement matrix from the T-100 Segment database. Detailed discussions of these two calibration phases are provided next.

5.2.2.1 Phase I: Subagent Functionality Calibration

The functionalities of the pricing and routing subagents were thoroughly discussed in the previous section and collectively they are responsible for instilling the agent adaptive mechanism in the TransNet methodology. Preliminary examinations and exercises of the pricing subagent were reported in Lim et al. (2006, 2007), where air service providers' pricing behaviors were shown to be reactive to the presence of competing air service providers. Coupled with the network adaptation model of the routing subagent, the Supply Calibration Phase I is aimed at demonstrating evidences of adaptive behaviors through the execution of the integrative demand-supply model.

A simulation experiment was created by adopting a *groundhog day* analogy, where the simulation was iterated over multiple identical cycles and the aforementioned adaptive mechanism of each service provider agent was allowed to perturb autonomously until observable trends were captured or when the maximum number of iterations was obtained. The simulation was designed to match the normalcy condition of a single-day NAS operation in the CONUS, where the number of true aviation demand is approximately 320,000 trips [1]. Note that each iteration was identical in that there were no transient factors considered whether in terms of population growths, income level growths, or time-value of money.

A hypothetical network model was generated by extracting a set of flight segment data within the CONUS from the T-100 database for the month of May in year 1995. Only services to and from primary hub airports with at least one flight daily were

[1] This approximation is made by extracting aviation demand count from the 1995 ATS on an average day.

sampled. This baseline network was then scaled down to reflect a single-day NAS capacity level representing an average day in the second quarter of year 1995. Four metrics were tracked for investigating the adaptive pricing and routing behaviors: Revenue Passenger Mile (RPM)-based market share, average return fare, average load factor, and $\frac{C}{E}$ where C and E are connecting and total passenger enplanements respectively. The $\frac{C}{E}$ metric is used to measure the significance of hubbing activities at a given airport or by a service provider (Yang et al., 2008).

Analysis of the average return fares for the service provider agents revealed several observations, one of which is that the average return fares for both legacy and low cost carriers tend to stabilize with more iterations as shown in Figure 45. The cyclical *jagged* trend observed on the fares data was due to the routing adaptation, which was prescribed to perform only after every fourth tick[2]. Fares were affected by this routing adaptation because the cost-based fare estimation used the average load factors from previous ticks to estimate cost per unit seat. A similar simulation was performed without activating the routing adaptation mechanism, resulting in non-repeating jagged trends but was deemed unfit for this calibration phase because the capacity levels were too mundane and exhibited no appreciable impact on the service network responses.

In general, this pricing adaptation can be thought of as the pricing subagent *learning* to make better price adjustments based on the perceived consumers' willingness to pay. Figure 45 shows that while the fare changes for both types of carriers appeared to follow the exact same trend, the resulting impact on their RPM market

[2]Significant schedule and fleet rearrangements are considered longer term actions which occur much less frequently than pricing actions. The simulation can be prescribed to invoke routing adaptation after any desired number of ticks.

shares were exactly opposite. The market share for low cost carriers was continuously rising at the expense of the legacy carriers. Intuitively, this could be attributed to the fact that low cost carriers offered lower average fares that appealed more to consumers at least while the routing subagent is still adjusting to find the most viable route network. In addition, the average fares for both carriers were shown to be converging towards steady state fares where the fare variances due to pricing and routing adaptations tend to diminish. Meanwhile, the comparison between average return fare for all service provider agents and air modes modal split was performed to study the impact of overall air fare changes to the modal split. Figure 46 shows that changes in the air modes modal splits were almost mirror images of changes in the air fares even though the magnitude of change was not proportionate. Besides showcasing the effects of the demand-supply interactions, this observation seemed to suggest that the impact of pricing adaptations is more direct and apparent than the impact of routing adaptations.

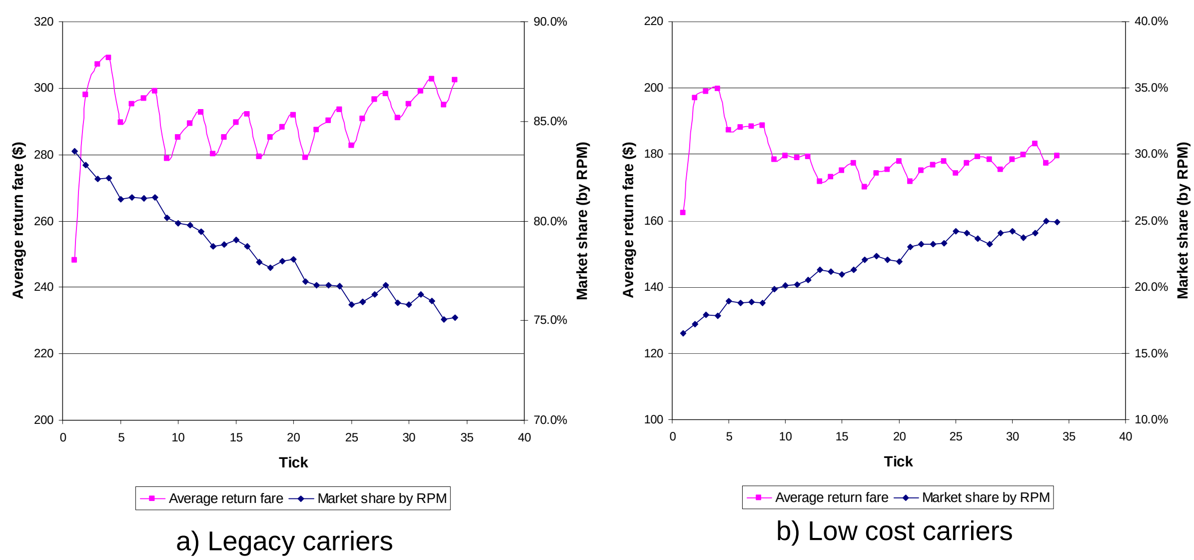


Figure 45: Supply Calibration Phase I: Average Return Fares and Market Shares

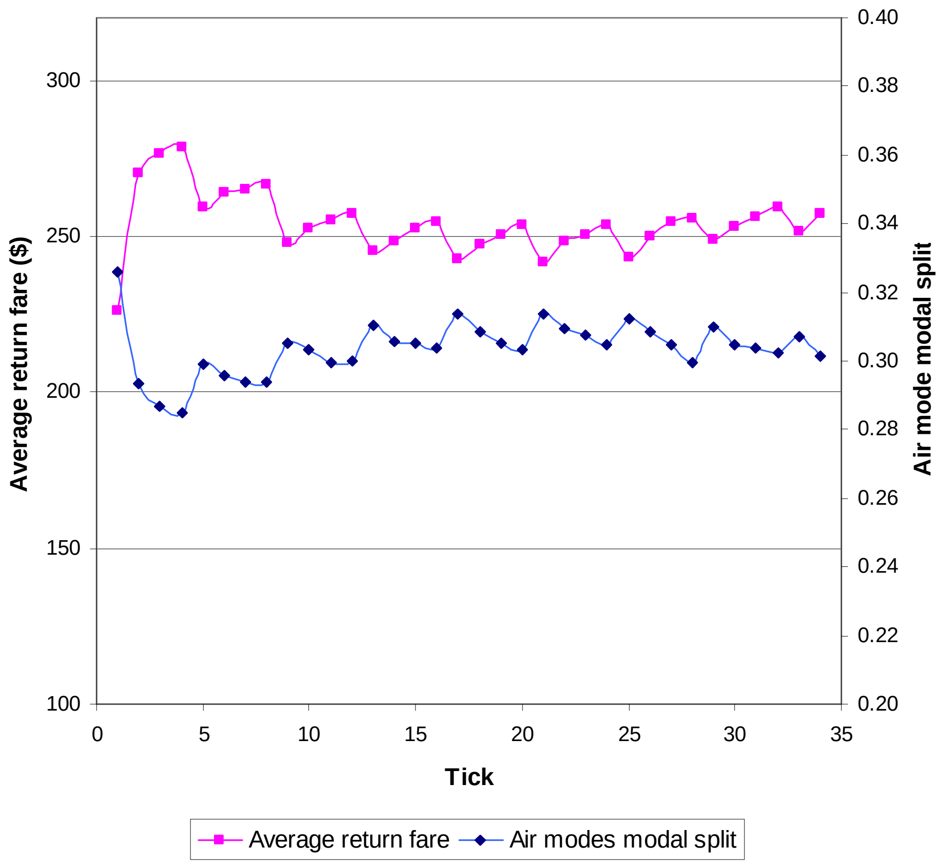


Figure 46: Supply Calibration Phase I: Average Return Fare and Air Modes Modal Split

Starting from a hypothetical service network model, the routing subagent proceeded to perturb routing parameters in search of a *stable* network system. A stable network system may be one that has a low variance average load factor. Since the pricing subagent computes base fares using previously experienced load factor values, a low variance average load factor translates to less variance in the pricing as well. Figure 47 shows that average load factors for both service provider types tend to stabilize with increasing iterations. Note that the absolute magnitude of the load factors in this calibration phase has little significance as the service network model was hypothetically generated to mainly investigate adaptive behaviors without attempting to match the real world data.

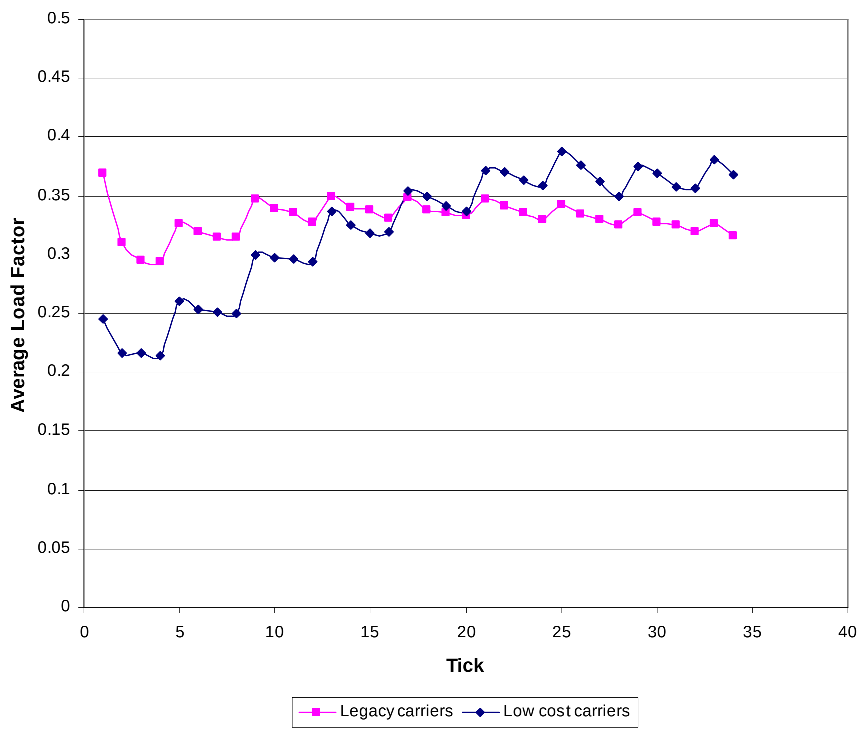


Figure 47: Supply Calibration Phase I: Average Load Factors

Along the lines of route adaptation, the $\frac{C}{E}$ values for legacy carriers were observed to have increased distinctively with increasing iterations. Since no active rules were embedded in the model to lead legacy carriers towards stronger hubbing activities, this observation is perceived as one of the emerging or self-organizing behaviors of the agent-based simulation. Under the circumstances defined by the hypothetical network system, legacy carriers inherently favored the hub-and-spoke system at least via the ϵ-greedy revenue maximization strategy prescribed to the agents.

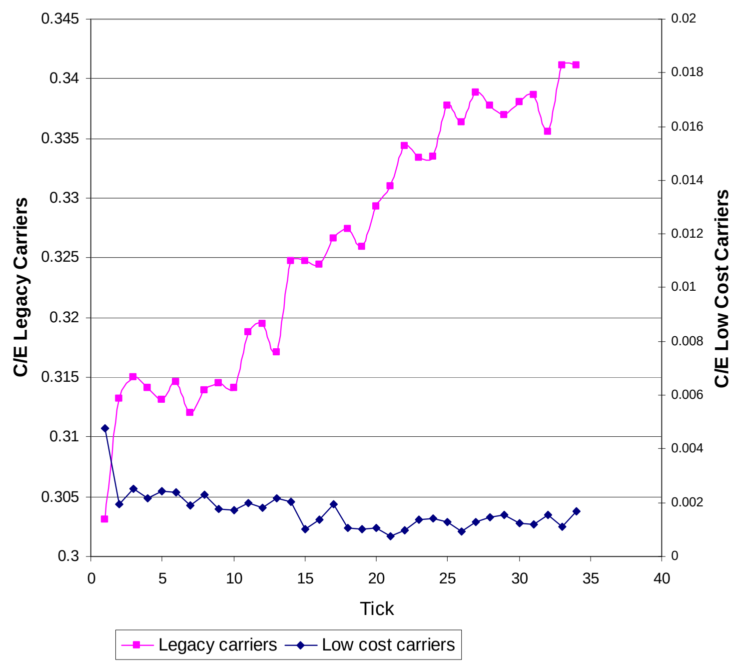


Figure 48: Supply Calibration Phase I: Connecting to Total Enplanement Ratio

Analysis of the simulation outcomes revealed evidences that the adaptive behaviors of airlines' pricing and routing were indeed captured by the integrative demand-supply model, particularly in terms of price competition between service providers, the convergence towards a stable network system, and the tendency towards hubbing by legacy carriers.

5.2.2.2 *Phase II: Baseline Network Generation Calibration*

The Supply Calibration Phase II was designed to address the proposition in **Hypothesis 4**, which states that the baseline supply model can be validated against the benchmark true aviation demand, $\tau_{ij,av}$ within tolerance in terms of the enplanement traits. Concurrently, the resulting enplanement matrix from the simulation must be comparable to the enplanement matrix extracted from the T-100 Segment database. The outcome would be a set of pricing and routing parameters that produces a baseline commercial air transportation network system that is representative of the air transportation supply observed in the NAS for the given base year.

Unlike in Phase I, the calibration process in Phase II was not fully autonomous and required some interactions and supervision from the developer in tweaking the model parameters. The initial baseline network was generated by extracting a set of flight segment data within the CONUS from the T-100 database for the month of May in year 1995. An initial parameter setting was estimated and the simulation experiment was performed in a static environment using $\tau_{ij,av}$ as the aviation demand input. The predicted enplanement matrix from the simulation was then compared against the enplanement matrix extracted from the T-100 Segment database. A brief discussion is needed to clarify possible confusions and debates in regards to using the T-100 Segment data source both for constructing the baseline network as well as for calibrating the enplanement matrix. From the object-oriented modeling perspective, Segmentobjects are non-stop flight segments directly derived from the T-100 Segment database. A collection of Segmentobjects creates a Routeobject, which in this research is restricted to either a direct route (with one Segmentobject utilized) or a single-connection route (with two connected Segmentobjects utilized). Aviation demand is translated into enplanements when Servprovagents execute the demand into their individual network via Routeobjects. The clarifying point is that *no enplanement information was absorbed from the T-100 Segment database into constructing the hypothetical route generation algorithm.*

Having clarified the above, the calibration results demonstrated close comparisons between the simulated enplanements and the actual enplanements recorded in the T-100 Segment database. Figure 49 shows that the predicted L-strip sum CDF for total passenger enplanements matched well against the observed L-strip sum CDF for total passenger enplanements. The comparison of percentage passenger enplanements shown in Figure 50 also revealed a close proximity between the predicted and observed data. The logarithmic scale plot on the right provides a closer look into the percentage passenger enplanements of the higher ranked locales and shows a better fit between the predicted and observed data. These comparison results provided the necessary evidences for validating the routing subagent.

Figure 49: Supply Calibration Phase II: Cumulative Distribution Function for Total Passenger Enplanements

These reported results served as strong evidences in proving the second part of

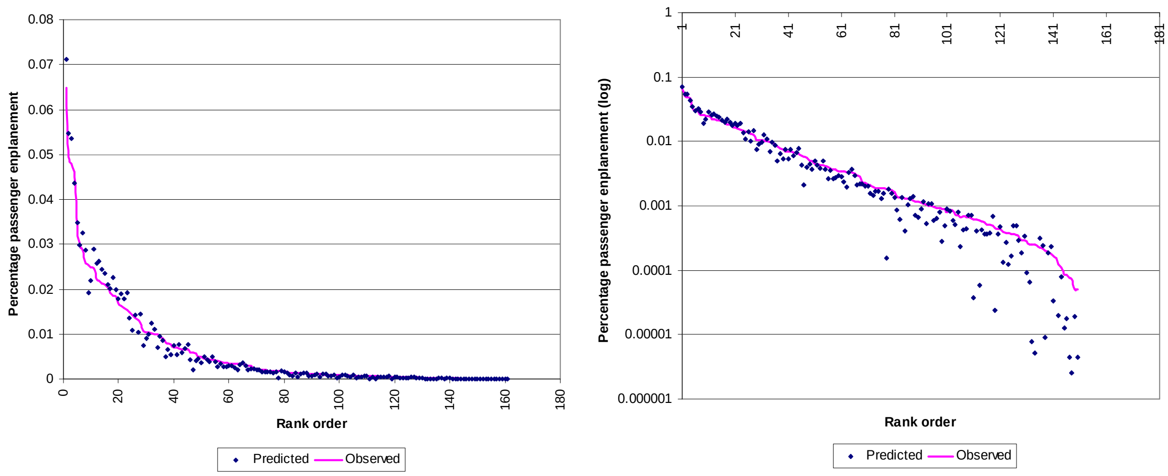


Figure 50: Supply Calibration Phase II: Percentage Passenger Enplanements

Hypothesis 4, in that the true aviation O-D demand $\tau_{ij,av}$ can be sufficiently captured by the supply model while matching the key enplanement traits of the network system.

CHAPTER VI

SIMULATION STUDY

With the verification and validation of the TransNet methodology through the successful calibration of the base model, the bulk of the research questions and hypotheses posed in Section 2.4 have been addressed. A simulation study was performed next as a demonstration on how the methodology could be utilized as the simulation engine for performing scenario studies and sensitivity analysis.

The simulation study performed is a 20-year forward outlook simulation of the U.S. CATS starting from the base year of 1995 and is comprised of two scenarios: i) *Business As Usual* scenario and ii) *Rising Fuel Price* scenario.

6.1 Business As Usual Scenario

As the name suggests, the *Business As Usual* scenario is intended to simulate transportation activities within the CONUS under normal operating conditions where:

- All the relevant population, economic, and price index growth rates follow averaging trends.
- The number of trips simulated approximates the average daily trip count in the CONUS under normalcy conditions.
- The simulated average fare is calibrated to approximate the observed national average fare for domestic air travel.

For this scenario simulation, both the pricing and routing subagent were prescribed to make adaptive changes during every simulation tick, where each simulation tick is equivalent to one quarter of a year. The decision to activate the routing subagent at every tick was founded based on the observations made from the calibration effort discussed in Section 5, where a cyclical trend was resulted due to the overpowering impact of the routing adaptation mechanism at every fourth tick. With this new approach, the cyclical trend is not expected to appear.

The first look at the simulation outcome emphasized the evolving fares for both legacy and low cost carriers as shown in Figure 51. As expected, the *learning* phase of the simulation within the first 8 simulation ticks (1995 to 1997) depicted significantly more volatile fare changes than the remaining years where more stable average fares were attained by the pricing mechanism. Besides that, the predicted average fare was shown to be in close proximity of the observed average fare for domestic air travel as reported by the Bureau of Transportation Statistics, which reinforced the validity of the model in approximating the proxy world.

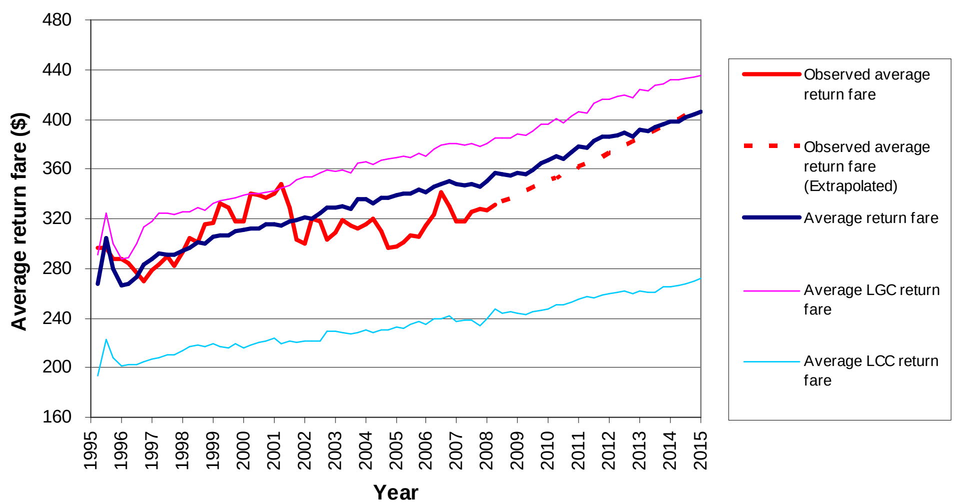


Figure 51: Business As Usual: Predicted and Observed Average Fares

Apart from approximating the observed average fare, an investigation into the revenue performances of the service provider agents was also necessary. Direct analysis of total revenues was unsuitable since the revenue gains due to the system-wide increase in demand cannot be isolated. Thus, the Revenues per ASM (RASM) performance was used as the measure of merit such that the capacity expansion actions by the routing subagent were also addressed. Due to the seasonality factors in air transportation demand, a year-over-year (YoY) comparison becomes the industry standard for performing comparative analysis of RASM and most other airline performance-related measures. Except during the first few years when the subagents attempt to attain stabilized fares, both legacy and low cost carriers recorded positive growths for most of simulation period, denoted as points above the thick red line in Figure 52. Evidence of RASM improvements in coherence with the top level revenue maximization goal of the service provider agent is showcased with this observation. The successful implementation of the agents' learning mechanism via information bank updates is also demonstrated.

Dwelling into the price competition between legacy and low cost carriers, Figure 53 shows that while average fares increased over the years, the battle for market share was also persistently ongoing. Fluctuations in the market shares was observed to decline over time, implying signs of market saturation and maturation as one would expect from a free competition economic system. The capability of the integrative demand-supply algorithm in portraying transportation market dynamics is further confirmed with this observation.

Having discussed the pricing adaptations, the operational adaptations of the service provider agents in terms of the route structure and capacity level are discussed next. Figure 54 shows snapshots of the route maps for legacy carriers at different progressions of the simulation timeline: the baseline network model (Baseline at tick

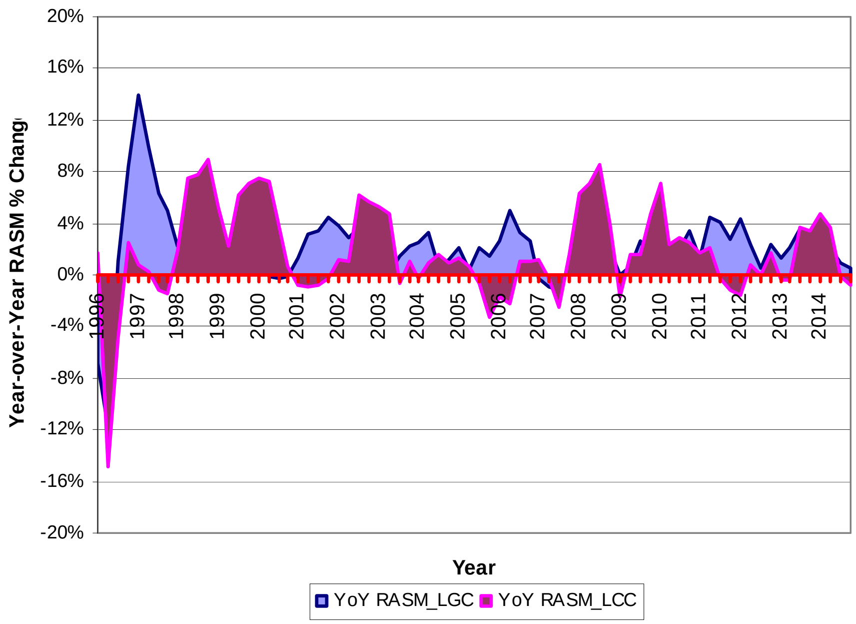
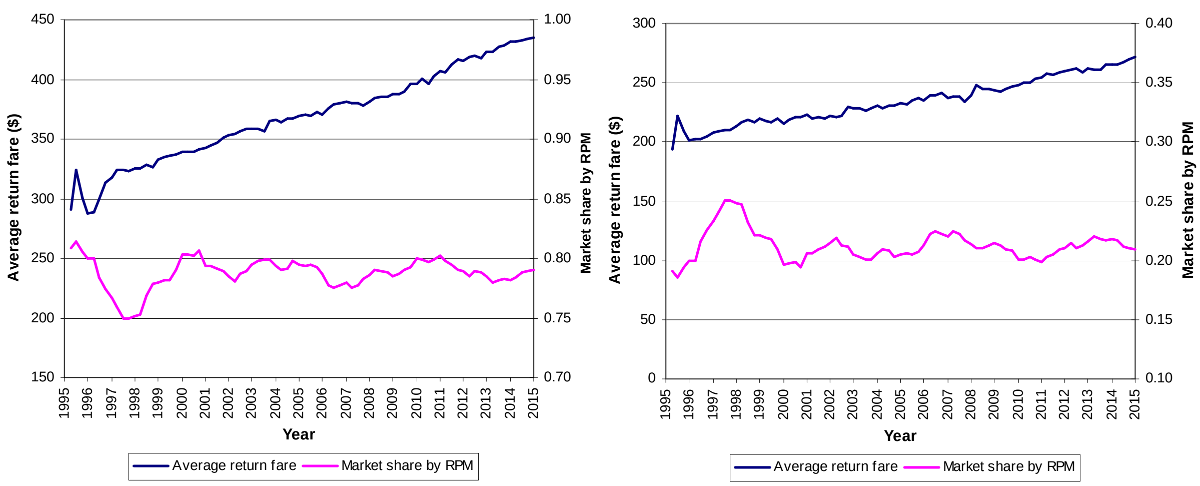


Figure 52: Business As Usual: Year-over-Year RASM Performance



a) Legacy carriers

b) Low cost carriers

Figure 53: Business As Usual: Average Fares and Market Share by RPM

= 0), first quarter of 1996 (1996 Q1 at tick = 5), first quarter of 2006 (2006 Q1 at tick = 40) and last quarter of 2015 (2015 Q4 at tick = 80 and end of simulation). These route maps are color-coded to depict the capacity level for each flight segment, where white indicates the lowest capacity level and darker shades of blue indicate higher capacity levels.

From Figure 54, it can be observed that the dramatic change in the route map from Baseline to 1996 Q1 particularly from the capacity level standpoint implied that a significant amount of routing adaptation has occurred within the first four ticks of the simulation. In addition, the capacity levels increased in high demand growth and more important key hub markets such as Los Angeles, New York, Seattle, and Atlanta. This showcased the positive reinforcements on operational efficiencies of the hub-and-spokes system due to the routing adaptation mechanism. Lastly, while not eminently depicted, the final route map at 2015 Q4 tend to visually approximate the route map of 1996 Q1 rather than 2006 Q1 at least from the network density and capacity level perspectives. This could imply that the legacy carrier network capacity does not converge nor conform in a unidirectional manner, rather, it is highly responsive to competition and demand fluctuations.

Continuing on the notion of network capacity but at the aggregated level, Figure 55 highlighted the operational adaptations made by the carriers by depicting high variabilities in the average load factors values. While price competition may partially explain the fluctuations, one would generally expect the average load factor to gradually increase as demand increases over time in a capacity limited system. The explanation offered for this observation is that the increasing demand and favorable transportation marketplace encouraged rapid capacity expansion by both carriers while remaining within the capacity limits imposed on the routing subagent (see Section 4.2.2. When both ASMs and RPMs are rising, the effective increase in average

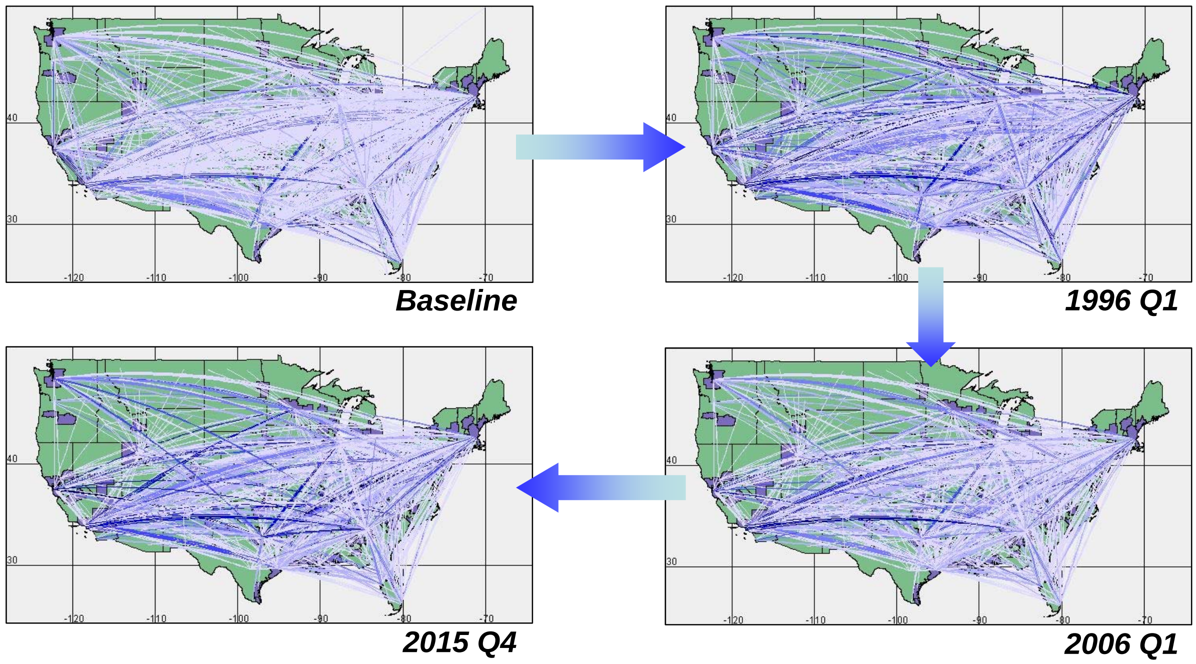


Figure 54: Simulation Route Maps for Legacy Carriers

load factor is naturally diminished. Figure 55 also shows the $\frac{C}{E}$ for legacy carriers[1] gravitating to a steady-state value of approximately 0.33, implying that the threshold for connecting operations remained at around 33 percent of total enplanements.

Figure 56 shows snapshots of the route maps for low cost carriers for the same simulation timeline as the legacy carriers. The first observation made is the dramatic change in the route map from Baseline to 1996 Q1, further supporting the previous observation in that a significant amount of routing adaptation occurred within the first four ticks of the simulation. The evolving route maps also show the formation of a *golden triangle* zone between Chicago, New York City, and Atlanta/Orlando/Miami; the three regions with the most intense low cost carrier operations in the East Coast. Evidently, this observation is aligned with the primary business policy of low cost carriers of focusing growths in high O-D demand markets.

[1] $\frac{C}{E}$ for low cost carriers almost always approaches zero due to the non-hubbing nature of their operational network.

Figure 55: Business As Usual: Average Load Factors and Average $\frac{C}{E}$

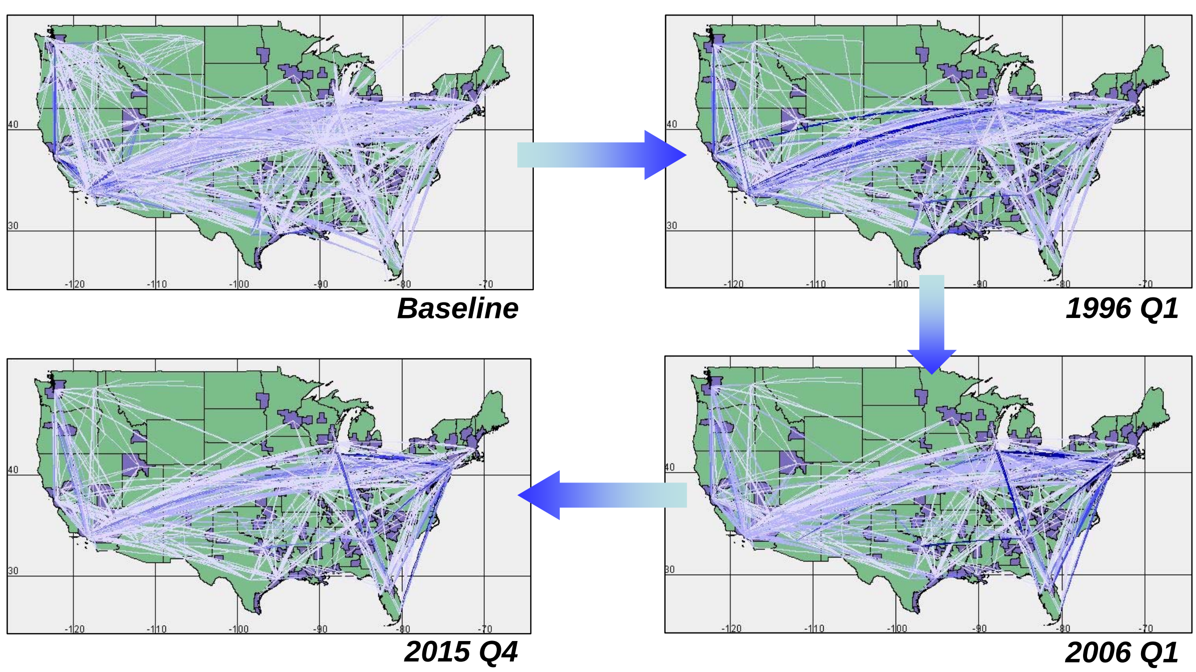


Figure 56: Simulation Route Maps for Low Cost Carriers

Lastly, the implication of increasing average return fare at the multimodal level is shown in Figure 57. Despite the rise in fares, the air mode modal split continued to increase but showed preliminary signs of tapering off to a steady-state value towards the end of the simulation period. This observation showcased the importance of inserting ground modes as competing transportation modes, without which fares would continue to increase without capturing the multimodal mode selection reactions and behaviors from these utility-driven consumer agents.

The outcome of the *Business As Usual* scenario simulation has yielded observations that reinforced the validity of key model components and provided insights into the forecasted 20-year outlook of the U.S. CATS. The simulation outcome also served as the control set for analyzing the *Rising Fuel Price* scenario, to be discussed next.

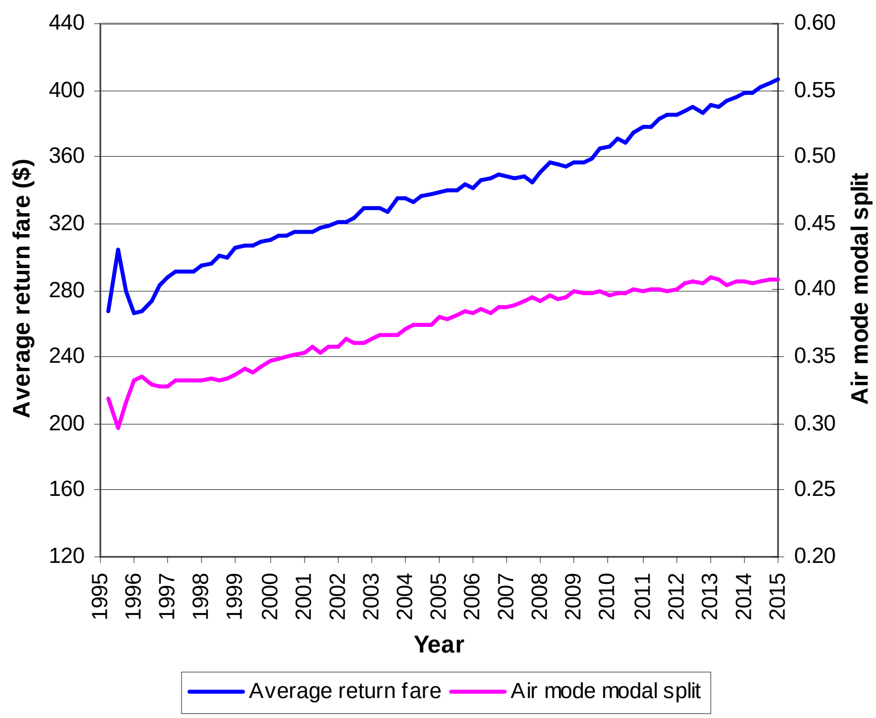


Figure 57: Business As Usual: Average Return Fare and Air Mode Modal Split

6.2 Rising Fuel Price Scenario

From 1995 to 2003, the global price of crude oil hovered between USD 15 and USD 30 per barrel. The second quarter of 2004 marked the beginning of a new era for crude oil trading where double digit annual price hikes were recorded for the years to come. The constant surge in demand coupled with heavy speculative trading of crude oil eventually led to the notorious spike in fuel price beginning in 2007, which peaked at USD 137 in the first week of July 2008 (Energy Information Administration, 2008). With fuel cost being one of the largest component of direct operating cost, the airline industry paid dearly for this economic calamity where more than a dozen U.S. airlines had seized operations since 2007. This phenomena thus, served as the motivation for the *Rising Fuel Price* scenario.

This scenario was formulated from the same ground assumptions as the *Business As Usual* scenario but with the additional condition where that the global price hike of crude oil has caused a dramatic increase in airline operating costs. A fuel cost multiplier schedule was populated to replicate the increase in fuel component of operating cost at the beginning of every new quarter (equivalent to one simulation tick) beginning from the first quarter of 1996. The schedule is depicted in Figure 58 where the fuel cost multiplier equals to 4.3 from tick 30 onwards. As mentioned earlier, the *Business As Usual* scenario simulation was used as the control set for analyzing this scenario simulation. The simulated *Business As Usual* and *Rising Fuel Price* scenarios are abbreviated as *S1* and *S2* for the remaining discussions in this section. All the scenario-by-scenario comparison plots were scaled to have the proportionate magnitude on the y-axis to enable direct scalar comparisons. In addition, it is noteworthy to point out that the transportation demand volume may decline under this scenario since the mobility budget constraint will inevitably reduce the number of feasible trips when fares increase (See 3.3).

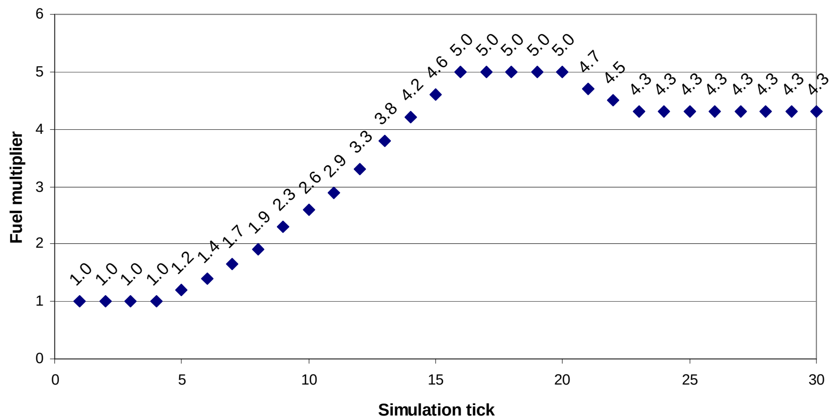


Figure 58: Rising Fuel Price: Fuel Cost Multiplier Schedule

Figure 59 shows that the average return fares for both legacy and low cost carriers were higher in scenario *S2* than in scenario *S1* due to the higher costs involved. A greater average fare gap was observed for legacy carriers since the fuel cost component was appreciably larger compared to low cost carriers. Concurrently, the higher average return fares of legacy carriers translates to a larger loss in market share to the low cost carriers as shown in Figure 60; the effects of price competition between the two carrier types is hereby observed again.

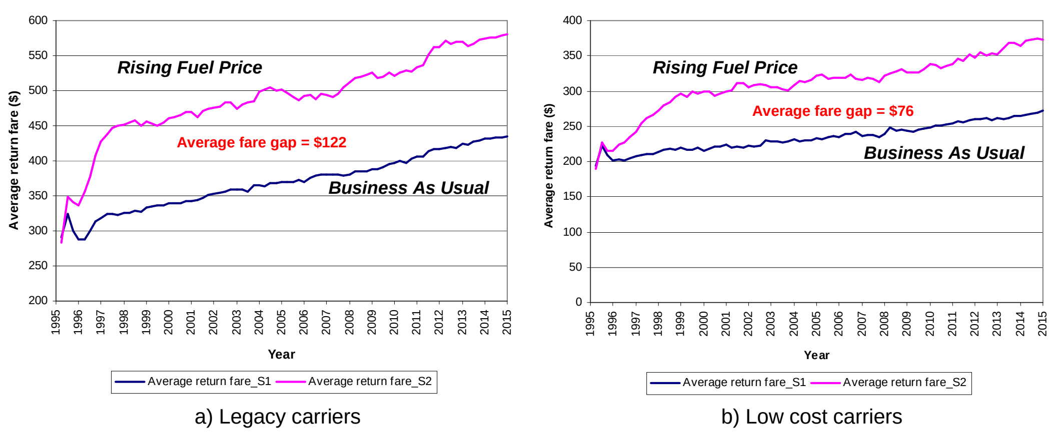


Figure 59: Rising Fuel Price: Average Return Fares

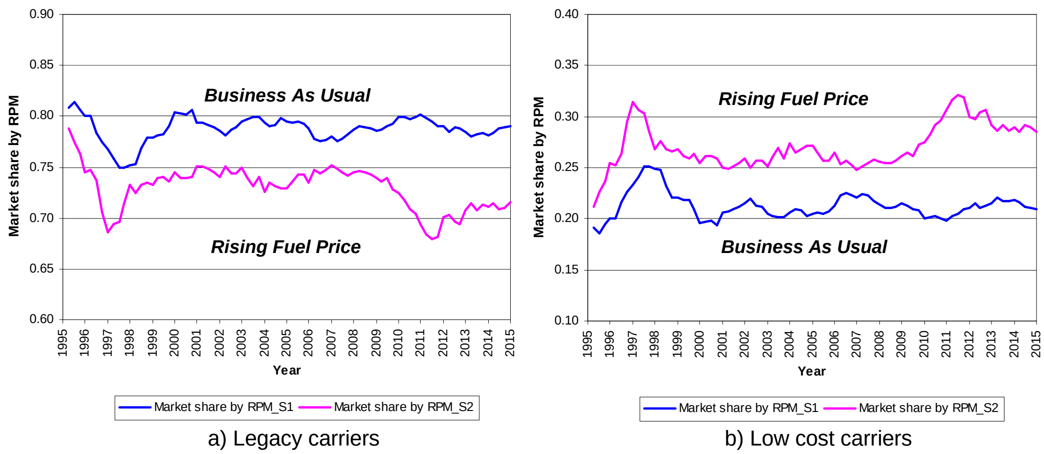


Figure 60: Rising Fuel Price: Market Share By RPM

The year-over-year RASM performance analysis is depicted in Figure 61. Disregarding the large spikes in the first few years of simulation, the overall YoY RASM performances in both scenarios *S1* and *S2* were not significantly different albeit more frequent negative growths periods in scenario *S2*. Under a fixed capacity condition, the rise in air fares would lead to a direct increase in revenues and subsequently better RASM performance. However, since capacity was autonomously perturbed in both scenarios, no further inferences could be explicitly drawn on the YoY RASM comparisons.

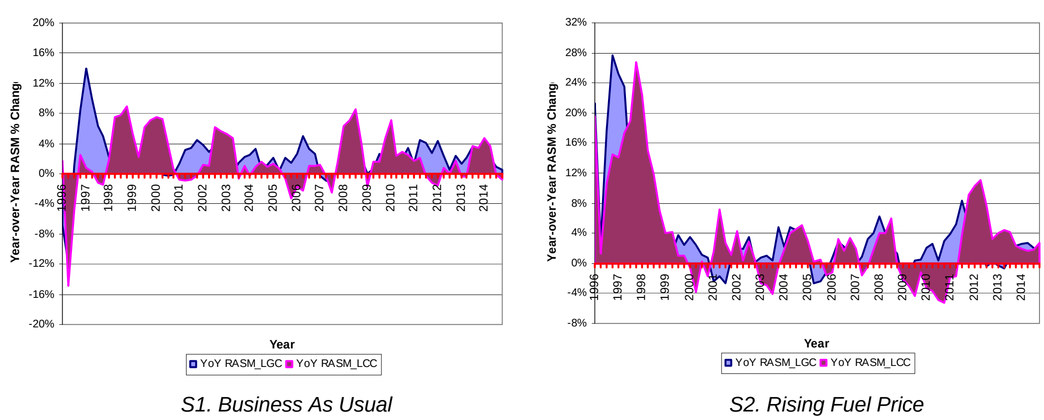


Figure 61: Rising Fuel Price: Year-over-Year RASM Performance

Moving on to investigating the operational adaptations by the service provider agents, Figure 62 shows the side-by-side comparison of the simulation route maps for legacy carriers between scenario *S1* and *S2*. The main observation is that the scenario *S1* route network is visibly denser than the scenario *S2* route network. Since darker blue lines particularly between known hub MSAs are more evident in the scenario *S2* route network, the hypothesis offered is that capacity expansion would be less favorable under a high cost operating condition, resulting in the need to more efficiently utilize the existing aircraft seat inventory through economies of scale; the founding theory behind the hub-and-spokes system[2]. To further support this hypothesis, Figure 63 shows that the average load factors for both carrier types in *S2* have been gradually increasing over time as compared to the flat trend observed from scenario *S1*. These average load factor values have also surpassed the steady-state values observed in scenario *S1*. Besides that, the steady-state value for legacy carriers' $\frac{C}{E}$ was observed to be higher in scenario *S2* than in scenario *S1*. This observation could be interpreted as consumer agents having to learn to choose the typically cheaper connecting flights over non-stop flights, indicating that the model successfully captured the mode choice selection behavior of cost-sensitive consumer agents.

Figure 64 shows the side-by-side comparison of the simulation route maps for low cost carriers between scenario *S1* and *S2*. From this comparison, the darker blue lines implied higher capacity levels for low cost carriers in scenario *S2* than in scenario *S1*, demonstrating evident market share gains by the low cost carriers in the event of rising fuel cost component.

[2] In light of the global oil price crisis, network carriers in the U.S. have dramatically reduced flight frequencies and even terminated services to lower demand markets in 2008 simply because the break even load factor has spiked due to the ballooning fuel cost.

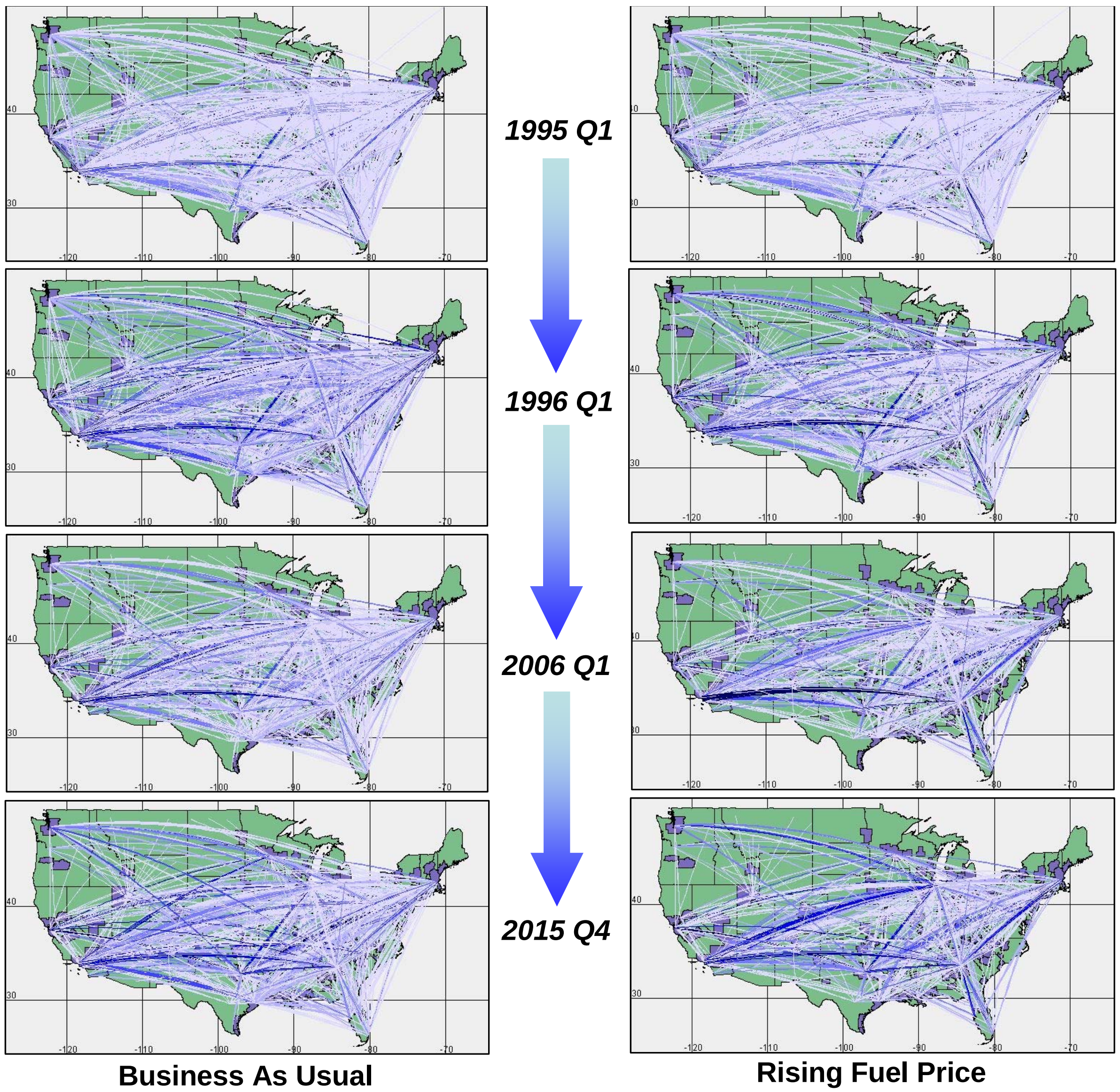
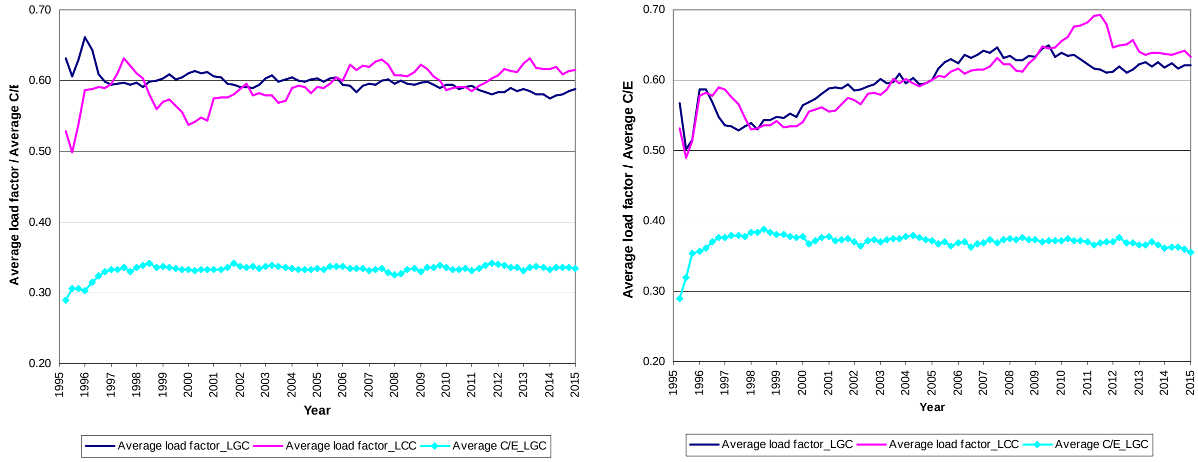


Figure 62: Simulation Route Maps for Legacy Carriers



S1. Business As Usual *S2. Rising Fuel Price*

Figure 63: Rising Fuel Price: Average Load Factors and Average $\frac{C}{E}$

Lastly, Figure 65 shows the implication of increasing average return fare at the multimodal level. Similar to the observation made for scenario *S1*, the air mode modal split in scenario *S2* continued to increase but showed preliminary signs of tapering off to a steady-state value towards the end of the simulation period. More importantly, an appreciable dip in modal split is shown beginning in year 1996 when the fuel cost multiplier began to take effect. This dip did not recover until almost four years later in 2000 when the fuel cost multiplier declined from 5.0 to stagnate at 4.3 times the 1995 fuel cost throughout the remaining simulation. This observation demonstrated the highly responsive reactions of consumer agents when a system-wide price hike is detected, triggering an eventual demand shift from air to ground modes. This observation is a highly valuable finding in verifying the pivotal role played by multimodal transportation relationships. However, it is more important to observe the responsiveness of the air transportation marketplace towards economic uncertainties and that the market dynamics eventually resulted in air transportation modes recovering and recouping modal split shares amidst a continuously higher cost environment relative to year 1995.

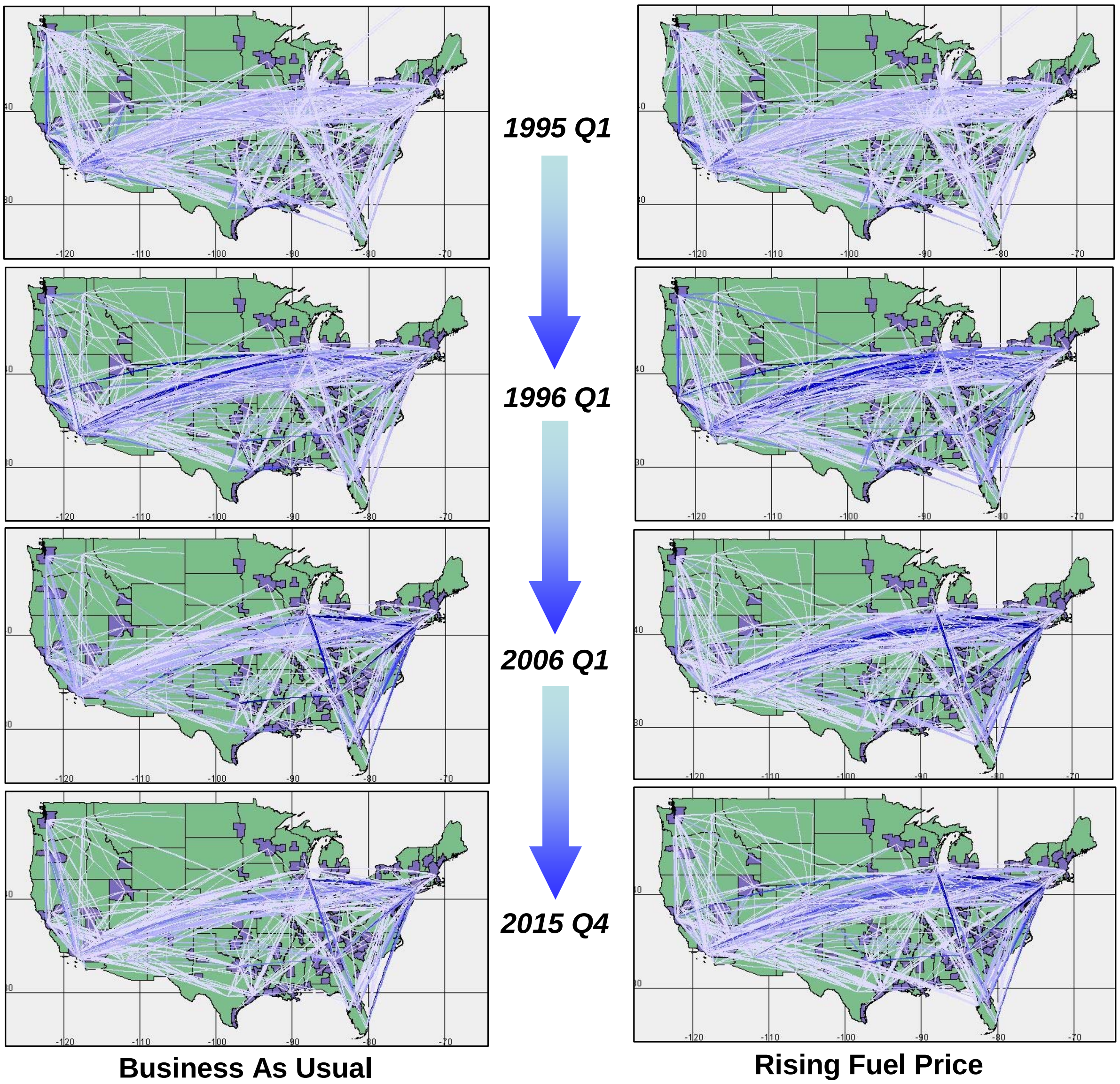


Figure 64: Simulation Route Maps for Low Cost Carriers

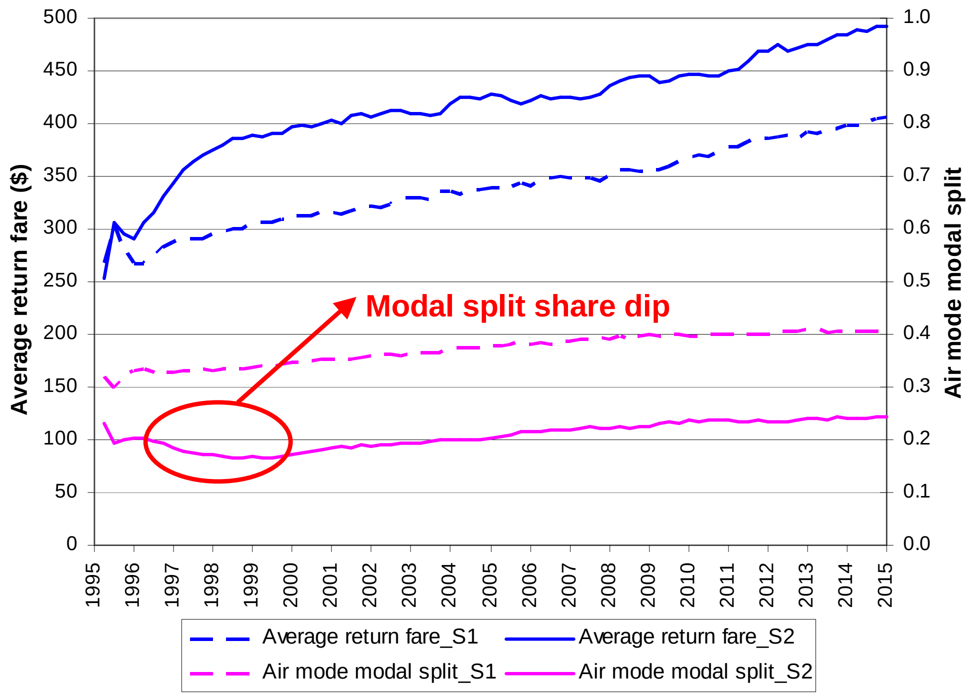


Figure 65: Rising Fuel Price: Average Return Fare and Air Mode Modal Split

6.3 Simulation Summary

In closure, the combined outcomes of both the *Business As Usual* and *Rising Fuel Price* scenario simulations have provided many reassuring observations of the capability of the model and the methodology. First, the observed average fare for air travel in the CONUS was closely approximated by the simulation outcome. The mode choice behavior of consumer agents was then observed from the analysis of competing multimodal transportation solutions as well as competing flight route options (non-stop vs. connecting between different carrier types). From the supply-side, the revenue maximization goal of service provider agents was showcased through the improving RASM performances by the carriers. The presence of price competition between service provider agents was demonstrated from the analysis of the fares and market shares dynamics. The operational adaptiveness of service provider agents was observed from the analysis of the average load factors and hubbing activities. Last but not least, the role of multimodal relationship in transportation demand-supply forecasting was highlighted from the analysis of the modal split behaviors between different transportation modes.

Based on the sensitivity analysis of the two scenarios, several inferences were made in regards to the transportation system behaviors and the constituting agents that generate these behaviors. First, the cost competitiveness of low cost carriers was shown to be highly advantageous in gaining market shares from the legacy carriers in an elevated cost environment. Meanwhile, legacy carriers (and possibly cost-sensitive consumers alike) preferred higher hub-and-spokes activities (higher $\frac{C}{E}$) in an elevated cost environment. Concurrently, both legacy and low cost carriers also increased efforts to fill up aircrafts (higher load factor) to mediate the higher operating cost. Consumer agents were shown to be highly responsive to sharp increases in fares and have a tendency to deflect towards employing ground transportation modes under such circumstances. However, the deflection was not permanent as air transportation modal split was shown to eventually rise even though fares were still at levels higher than the base year 1995. Based on these findings, one could even infer that for long distance trips greater than 100 miles, air transportation modes will not be noticeably substituted by ground transportation modes in the long run despite elevated air fares.

CHAPTER VII

CONCLUSIONS & RECOMMENDATIONS

7.1 Revisiting Research Questions & Hypotheses

The process of calibrating, verifying, and validating the components of the TransNet methodology was one that is no less important and rigorous as the implementation itself. Along with the observations and inferences made during the simulation study, the research questions and the corresponding hypotheses posed in Section 2.4 are revisited in this section with discussions made from the viewpoint of the scientific achievements attained from this dissertation. The four hypotheses were formulated and presented in the order of highest level hypothesis first starting with **Hypothesis 1**, which addresses the overall complex adaptive nature of the CATS. However, the testification of these hypotheses are presented in the reverse order starting with the lowest level **Hypothesis 4**, which goes into the verification and validation process of the integrative demand-supply model, followed by **Hypothesis 3** on the focus on the airline pricing and routing functions in capturing the competitive nature of service provider agents. Only then can **Hypothesis 2.1** and **Hypothesis 2.2** on the approach and level of granularity for modeling transportation demand be testified. Lastly, **Hypothesis 1.1** and **Hypothesis 1.2** can be testified to reveal whether or not the bottom-up network modeling platform and the integrative demand-supply model are capable of reflecting complexity and competition in the CATS.

With the integrative demand-supply model at the heart of the TransNet methodology, it is equally important to showcase the veracity and validity of the model as it is to profess its capabilities. This led to the formulation of the following research question and hypothesis:

> **Research Question 4.** *How can the validation and verification effort of the integrative demand-supply model be made more tractable?*
>
> **Hypothesis 4.** The integrative demand-supply model can be decoupled to independently calibrate and validate the demand model and supply model against proxy world data sets. If the decoupled models can be independently calibrated and validated, then the integrative demand-supply model is also validated.
>
> **Supplementary Question 4a.** *What are the calibration and validation criteria for the transportation demand model?*
>
> **Supplementary Question 4b.** *What are the calibration and validation criteria for the transportation supply model?*

By decoupling the integrative model as posited by **Hypothesis 4**, Demand Calibration Phase I and II (Section 5.2.1.1 and 5.2.1.2) demonstrated the veracity of the consumer agents' mode choice and demand distribution mechanism while Supply Calibration Phase I (Section 5.2.2.1) demonstrated the veracity of the service provider agents' functionalities. The demand model was then calibrated against the superset aviation O-D demand data in Demand Calibration Phase III (Section 5.2.1.3), in which the demand model was shown to be capable of generating hypothetical aviation demand that is matched well against the proxy world data. Moving on to the supply model, using the superset aviation demand as input demand, Supply Calibration Phase II (Section 5.2.2.2) showed that the total passenger enplanements generated from the supply model matched well against the real world enplanement data observed from the T-100 Segment database. Extending these two verification and validation results to the overall integrative model, the outcomes from the *Business As Usual* scenario simulation (Section 6.1) not only showcased predicted average return fares that are highly representative of the observed historical air fares in the U.S., but also yielded several observations that had reassured the model's capability to reflect anticipated behaviors in terms of multimodal transportation relationships, price competition, and market dynamics at large. These outcomes collectively permitted the claim of weak validation (as professed in Section 5.1) of the integrative demand-supply model and thus, **Hypothesis 4** is hereby deemed validated.

The third research question and corresponding hypothesis was founded based on the notion that airlines have complicated functions that are difficult to be fully modeled and a simplifying but accurate remedy is required:

Research Question 3. *Which functions are the most critical ones in reflecting the competitive behaviors of airlines?*

Hypothesis 3. The modeling of airline pricing and routing functions sufficiently captures the competitive behaviors or airlines at the industry level. Fleet / frequency selection and scheduling dwell into highly detailed operational activities at the vehicle level which are perceived to be beyond the scope of a nationwide system study.

The ability to represent all four core functions in the service provider agent construct would be an ideal solution. However, accessibility to the required amount of time, computational, and knowledge resources oftentimes create barriers from getting to the ideal solution. This hypothesis was posed after scrutinizing the possibilities of creating a simplified but accurate representation of the transportation supply-side component after having determined the scope of this research, in which vehicle level of details are not required let alone desired. There are two approaches for testifying against this hypothesis. For the first approach, all four airline core functions (pricing, routing, fleet/frequency selection, and scheduling) are modeled and the capability of using only pricing and routing functions to study airline competition can be compared against the capability of using all four functions. For the second approach, only the two premeditated core functions (pricing and routing) are modeled and the capability of the service provider model in displaying competitive behaviors is independently measured. Evidently, the first approach converges towards the aforementioned ideal solution, thus, the second approach is the more feasible approach for testifying the hypothesis.

Modeling of the two core airline functions as postulated by **Hypothesis 3** only fulfilled the supply-side components towards capturing competitive airline behaviors. The need to capture the spatially-explicit true origin-destination demand is required to capture the demand-side components, which gave rise to the formulation of the following research question and corresponding hypothesis:

Research Question 2.1. *What is the approach for capturing true origin-destination demand?*

Hypothesis 2.1. An agent-based approach that inherits trip distribution and mode selection techniques from the Four Step Model is adopted. This approach captures the behavioral aspects of transportation demand and is aligned with the bottom-up design framework posed by Hypothesis 1.1.

Research Question 2.2. *What is the minimum level of granularity required for modeling the spatially-explicit transportation environment?*

Hypothesis 2.2. The level of granularity at the Metropolitan Statistical Area level is required. Primary airports in these locales are used to represent the airport network system. This level of granularity is aligned with that of the 1995 American Travel Survey.

Outcomes from the *Business As Usual* and the *Rising Fuel Price* scenario simulation (Sections 6.1 and 6.2) provided strong evidences in support of the model's capability to demonstrate the competitive behaviors of airlines. These competitive behaviors were shown to cause variabilities in the average return fares of both legacy and low cost carriers despite an overall increasing trend, causing consumer agents to switch between the various service provider agents (as shown by the fluctuating market shares). When fuel cost was increased, aviation demand was also shown to deflect toward ground transportation mode for a short period of time. The different business policies, namely, cost structure, pricing structure, and network configuration, were also reflected into the various performance measures of carriers such as fares, RASM performance, and market share. Coupled with the verification of the various Demand and Supply Calibration Phases, the postulation made in **Hypothesis 2.1**, **Hypothesis 2.2**, and **Hypothesis 3** are hereby deemed validated.

The top level research question and corresponding hypothesis was founded based on the notion that the commercial air transportation system is a complex adaptive system:

Research Question 1. *How can one model the complex behavior of the commercial air transportation network system?*

Hypothesis 1. The complexity and competition in the system, both of which are time-dependent derivatives of the demand-supply interactions, must be addressed.

Research Question 1.1. *What is the modeling approach required for capturing complexity of the system?*

Hypothesis 1.1. A network modeling platform that adopts a bottom-up design framework is required. This approach addresses sentience at the constituent level where complex behaviors are derived.

Research Question 1.2. *How can airlines competition be reflected?*

Hypothesis 1.2. The market dynamics derived from the tightly-coupled interactions between airlines and consumers must be captured in order to reflect airlines competition. This is done via an integrative demand-supply model, which employs various transportation forecasting concepts, probabilistic methods, and learning techniques.

Supplementary Question 1.2a. *How does air service providers competition impact the travel demand and behavior of consumers?*

Supplementary Question 1.2b. *How are the different business policies reflected onto the financial performance of airlines?*

Discussions from Chapter 4 went through the thorough process of constructing the hypothetical CONUS transportation system network model from the foundation of a bottom-up agent-based design framework. The intertwining of demand-side and supply-side modules was deeply rooted into the formulated methodology since the conceptual design phase, with the sole objective of being able to demonstrate the time-variant complexity and competitive elements of the U.S. CATS. Supply Calibration Phase I (Section 5.2.2.1) provided fundamental evidences of the adaptive mechanism of the pricing and routing subagents and demonstrated the convergence of fares and market shares towards steady-state conditions. Observations made from the Simulation Study in Chapter 6 provided even more supporting evidences of the adaptive capabilities of the service provider agents. The Simulation Study also showcased multiple observations of competition between the two types of carriers along the lines of price and market share contentions. These competitive behaviors were only possible with the presence of direct and dynamic interactions between consumer agents and service provider agents with transportation activities as the final outcome. With the demonstration of complexity and competition in the system through the proclaimed methodology, **Hypothesis 1** along with **Hypothesis 1.1** and **Hypothesis 1.2** are hereby deemed validated.

The four research questions along with the supplementary questions have been addressed. A summary of the research contributions of this research is discussed next.

7.2 Research Contributions

The TransNet methodology is formulated to study the evolving U.S. CATS as a complex system-of-systems problem through multidisciplinary modeling and simulation. Areas of research that have contributed to and will likely to learn from this research include aviation system-of-systems, operations science and management, airline economics and competition, transportation demand modeling, and simulation design methodology among others.

This dissertation and the research involved are performed with the goal of formulating a hypothetical design methodology for studying the interactions between transportation demand and supply stakeholders in the commercial air transportation systems under a time-variant environment. One of the initial postulation which was eventually confirmed is that the interrelationships between consumers and service providers and the multimodal relationships with ground transportation modes play a pivotal role in the study of the commercial air transportation marketplace. No existing research has attempted to investigate these tightly coupled interactions under an integrative framework, thus making the TransNet methodology a significant contribution to the field of commercial air transportation systems research.

Another key contribution of the research is the accurate modeling of aviation demand forecasts at the NAS level that is not merely based on enplanement growth multiplier but on the socioeconomic and demographic properties of the population; a feat that cannot be undermined due to the highly complex structure and large geographic scope of the problem. The well-matched comparison between observed and predicted aviation demand data yielded great confidence in the veracity of the demand model component, allowing the TransNet methodology to be utilized for other aviation demand forecasting research.

The subsequent calibration of the supply model demonstrated the capability of using only pricing and routing functions to capture the gist of competition in the airline industry. Much like the numerous active complex adaptive system research in replicating the stock market and other economic systems, the hypothetical pricing and routing subagent concepts provided numerous insights into the aggregated relationships between legacy and low cost carriers that could pave the way for formulating a more complete and larger system of airline entities.

The tangible outcome of the TransNet methodology for this dissertation is an analysis tool that is capable of assessing the evolving U.S. commercial air transportation system. Selected scenarios simulated for this research have provided many insightful observations into answering the research questions posed as well as demonstrating strong potentials for extended research in this field of study. Subsequently, other studies with aligned research scope can be performed using this simulation model to provide better understandings of the air transportation dynamics within this highly complex system-of-system. Characterization for the research scope include spatially-explicit multimodal transportation analysis at the top level without dwelling into the low level vehicular and operational details. While scalar comparison with the proxy world data is important, the ability to observe behavioral trends between the interacting agents and their environments is also a key strength of this methodology.

Last but not least, the TransNet methodology is professed to be capable of generating a hypothetical commercial air transportation *living* system that is representative of the proxy world system, whether it be in the U.S. or other nations as long as synonymous construct and calibration data sets are first attained.

7.3 Recommendations

The utopian goal of the TransNet methodology is to facilitate more informed decision making for the different stakeholders of a CATS, whether in the specific aspect of reversing the fate of the declining airline industry, or in the holistic aspect of preparing for the rapid growth in aviation demand. One of the biggest gap identified before this goal can be achieved is that lack of air service provider representation. Service providers and their business models have evolved rapidly with changing times and economies, making legacy and low cost carrier classification an outdated way of distinguishing between carriers. The agent definition process for characterizing all the unique distinctions of carriers become an overwhelmingly large problem but remains as a highly intriguing research problem nonetheless.

Besides service provider agent definition, the consumer agent definition could also be further improved to reflect more realistic and deliberative demand patterns. While the TransNet methodology emphasized only on the advance purchase behavior, airlines are known to also use Saturday night stays and length of stay to better grasp the types of consumers at any given transaction point. Inclusion of these purchasing patterns may yield more realistic representation of commercial aviation demand. In addition, the consumer agents could be instilled with higher degrees of sentience by taking the large step towards retaining agents' purchasing memory; allowing purchasing behavior to be influenced by past travel and purchasing experiences.

There is also a dire need for transportation research community in the U.S. to push for a new set of national level transportation demand data other than the outdated 1995 ATS. With the new data set, the model can be calibrated at multiple points in time to enable more accurate transient analysis and forecasting.

While this research has instilled many transportation modeling concepts such as alternative airport selection and intermodal transportation relationships, much more development could be performed particularly in terms of the ability to infuse operational technology concepts for future transportation scenarios. Instead of merely providing fudge factors to certain operational variables, a more elaborate yet succinct method of introducing these new concepts can be an appealing feature for those studying game changing technologies.

APPENDIX A

AVIATION MODELS & DATABASES

A.1 Simulation Model: AvDemand

Simulation-based demand models generate NAS passenger demand by extrapolating a baseline flight demand set to future values via hypothetical demand growth factors. One of the most recent and representative state-of-the-art demand forecast simulation model is AvDemand (Huang et al., 2004), created by Sensis Corporation for NASA to provide NAS traffic demand predictions for evaluating futuristic and advanced concepts. An in-depth discussion of this model is provided to explain this demand forecast method.

AvDemand possesses an application library database that compiles existing data for airports, aircraft, airspace, waypoints, geographic and demographic profiles. It also receives input data in the forms of demand data (ETMS, ASDI, OAG, and DB1B), NAS data (NFDC and ASPM), environment data (RUC), concept input data, demand statistics data (ASPM and T-100), and aircraft performance data (BADA, aircraft manufacturers, and airline performance departments). The concept input data are provided by the user to define the specific advanced concept proposed for the simulation. AvDemand adopts a top-down approach for its flight-based demand generation, which assumes a baseline flight demand set and grows the future flight demand sets from that baseline. The user can assume either homogenous or heterogeneous airport growth rates in the studied region. The flight demand generation consists of the flight schedule generation and the flight plan generation.

The definition of the AvDemand's flight schedule attributes, such as aircraft flight ID, aircraft type, departure/arrival airports, and departure/arrival times follows a six-step process as shown in Figure 66. The first step generates the total number of flight/passenger trips for the given region via the flight-based demand generation approach mentioned earlier. The total trips are then distributed as directional traffic flows between airport pairs. Each airport pair now bears certain characteristics that serve as a comparison between airport pairs in the simulation and historical airport data. The next two steps are interchangeable; users can opt to first determine either the fleet mix or the flight frequency. Fleet mix for a given airport pair is described by the aircraft types and fleet mix percentages, which is determined using the historical market segment data (T-100 database) with similar airport pair characteristics. Flight frequency is also determined from the same data, but is expanded to accommodate the desired airport growth factor via the Fratar algorithm. The fifth step generates schedule times for each flight. The flight departure times can be distributed either using a uniform distribution function or an in-house stochastic process termed the Airport-Pair Demand Profiling. The last step involves an aircraft rotation model to ensure aircraft tail connectivity logics are enforced.

Upon completion of the flight schedule generation, the flight plan generation process in AvDemand computes the flight path, required amount of fuel, emergency destination options, specific flight-dependent information (e.g. radio frequencies, expected arrival times), and route description information (e.g. waypoints sequence, altitudes, Mach numbers, top-of-climb points, top-of-descent points). These are industry-standard specifications for prescribing the mechanical trip flight in the real

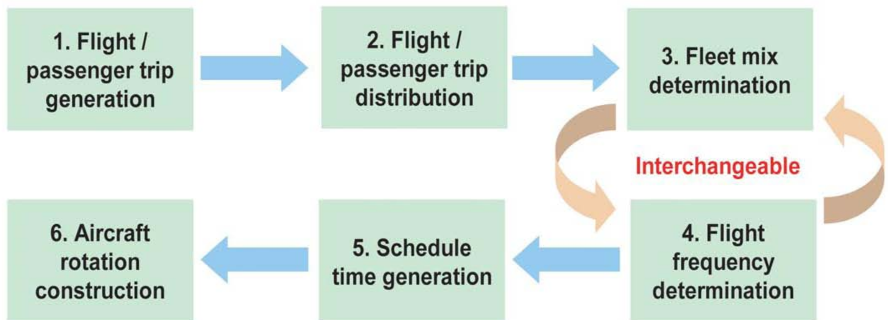


Figure 66: AvDemand Flight Schedule Generation Process Flow [Adapted from Schleicher (2004)]

world as well as in a simulated airspace environment, such that the output can be exported directly into other NAS models.

A.2 Transportation System Analysis Model (TSAM)

The Transportation System Analysis Model (Trani, 2006; Trani et al., 2004), is a database-driven simulation model originally developed at Virginia Tech to investigate the viability of NASA's Small Aircraft Transportation System (SATS) program. The primary focus of TSAM is to compute spatially-explicit demand for long distance trips greater than 100 miles (for both business and leisure travel) using socio-economic and demographic data at the 3091 counties in the CONUS. Subsequently, TSAM creates a 3091-by-3091 O-D matrix between these counties serving as the backbone of the highly detailed analysis. The foundational framework of this model is derived from a aforementioned Four Step Model. Figure 67 shows the structural layout of the model, with the list of reported models that are compatible with TSAM shown in the bottom.

In the Trip Generation module, TSAM uses historical correlations observed from the ATS data along with the income distribution from Census and the CEDDS (for future forecasts) databases to generate the total trips originating from each county.

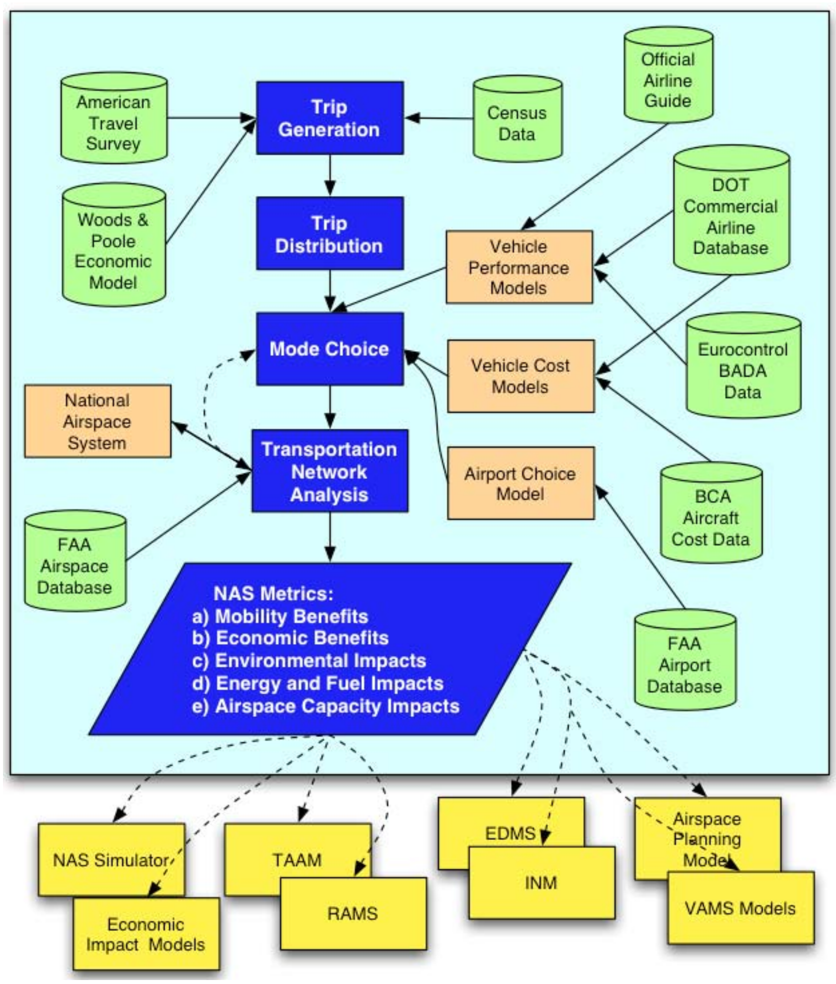


Figure 67: TSAM Structural Layout [Source: Trani (2006, p. 10)]

In the Trip Distribution module, the Gravity model is used to distribute the total trips to destination counties based on the economic and demographic properties of both counties. When the total trips have been distributed, the O-D matrix is created and calibrated against the aggregated state level trip distribution from the ATS data. Due to the large number of counties involved, the calibration of the trip distribution is very computationally expensive and time consuming. Thus, the matrix is carefully stored for use with the mode choice and trip assignment analysis provided the demographics and trip rate properties remain unchanged. In the Mode Selection module, TSAM uses a nested-logit model to predict the percentage of trips transported using each mode for the previously generated total trips. The model allows the mode choice between commercial airlines and automobiles as well as other SATS vehicle concepts. The travel costs and times, computed using the OAG and DB1B databases for airlines and Microsoft MapPoint for automobiles, are the key attributes used to determine the modal split for the region of interest. Airline travel time includes consideration for intermodal travel time (i.e. getting to and from the airport), processing time at airports, and slack time (i.e. unknown uncertainties allocated by traveler). Finally, in the Trip Assignment module, TSAM predicts flight trajectories and aircraft performance using tabulated data that are similar to the BADA model. To reinforce the strength of this model, a highly communicative interface is implemented such that users can effectively visualize the simulation process and outcome.

A.3 Mi

Mi (Lewe, 2005) is an agent-based model created at Georgia Tech. It creates a virtual NTS where agents live to imitate the transportation activities within the CONUS as a whole. Two groups of transportation stakeholders are included as the agents, namely, transportation consumers and transportation service providers. The transportation consumers are individuals or groups of individuals producing long distance travel demands, and are populated from either households or enterprises based on the demographic and economic data. The counterpart of the consumers is the transportation service providers that offer price and time information for trips based on their own mode and business model. The CONUS in *Mi* is categorized by generic locales, where all geographic areas under the Census 2000 correspond to one of the four locales: Large-, Medium-, Small-, or Non-metropolitan area. Origins and destinations within each locale share similar characteristics in terms of economic characteristics, accessibility to airports/highway, and other transient factors such as traffic delay. A functional process flow chart of the model is shown in Figure 68.

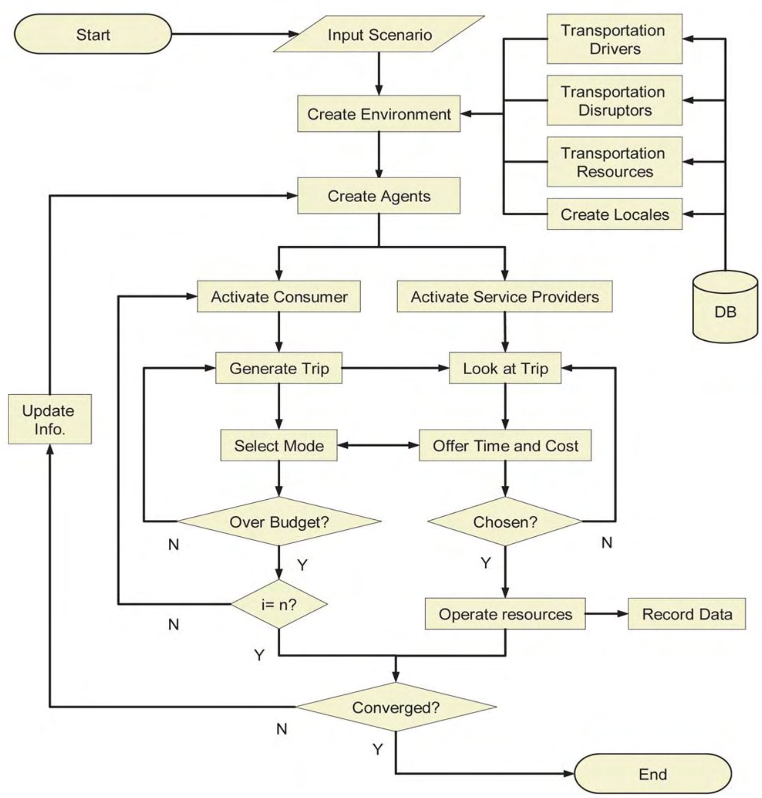


Figure 68: *Mi* Functional Process Flow [Source: Lewe (2005)]

In contrast to the aggregate representation of the locales, trips in *Mi* are generated at the microscopic agent level, where behavioral rules can be injected into the consumer agents' travel desire. To describe this behavioral process, assume an initial list of trip demands. All primary trip information (e.g. purpose of trip, destination, and distance) and secondary trip information (e.g. prospective travel dates and nights away at destination) are assigned for each demand. Then, the consumer goes through a mode choice selection process to match each demand's characteristics with a given set of modes. In the next step the consumer eliminates some trips under time and cost budget constraints to select a real travel demand. Finally, the consumer goes through a final decision process governed mostly by psychological factors due to uncertainties such as inclement weather and other disrupting events. Mode choice selection in *Mi* is comprised of two selections for each generated trip; a vehicle mode and a service provider. Four vehicle concepts are available to the consumers: automobile (CAR), commercial airline (ALN), single-class piston aircraft (GAP), and business jet-class aircraft (GAJ). On top of that, three service provider business models are offered: SELF - self owned/operated (CAR, GAP, GAJ only), RENT or HIRE - leased vehicles (CAR, GAP, GAJ only), and FARE - scheduled public transportation (ALN only). A disutility function is then computed for every possible combination of mode and business model and used as the basis for a nested multinomial logit (MNL) model. The overall mode choice selection module of *Mi* is calibrated using the ATS data as a baseline. Without a detailed prescription of the microscopic operations within the simulation, *Mi* demonstrated the emergence of a travel behavior that accurately reflects the actual modal splits pattern reported by the ATS data. The ability to capture this emerging behavior reinforced the validity of the model to forecast consumers' travel behavior within the CONUS for a given set of demographic and socio-economic characteristics.

A.4 Airspace Concepts Evaluation System (ACES)

The Airspace Concepts Evaluation System (Sweet et al., 2002) is a large scale, agent-based model created by the NASA Ames Research Center under the Virtual Airspace Modeling and Simulation project to reconstruct gate-to-gate actions between key participants within the NAS. This model performs a non-real-time evaluation of the system-wide NAS in order to assess the costs and benefits of new and revolutionary tools, concepts, and architectures. It is also used by the Joint Planning & Development Office (JPDO) to evaluate the baseline and future scenarios for the NAS. The architecture of this model is derived from a distributed simulation approach called the High Level Architecture (HLA) . This modular *plug and play* design allows for easy integration with other models having different levels of complexity (Roth and Miraflor, 2004).

There are three basic components within ACES: Agent, Environment, and Infrastructure. Three NAS participants are defined as agents; the air traffic control system, the aircraft, and the airline, and they are responsible for all gate-to-gate activities within the simulated NAS. The air traffic control agents are comprised of the airport, the ARTCC, the TRACON, and the Air Traffic Control System Command Center (ATCSCC). This structure essentially mimics the actual configuration of the air traffic control system, as discussed in Section 3.3.2.1. The airline is represented by the Airline Operations Center (AOC). Besides these NAS agents, there are internal agents that are responsible for simulation activities such as visualization and flight data distribution. These agents rely on a message flow system to facilitate the flow of information from one agent-activity to another, as shown in Figure 69. Meanwhile, the Environment models define the NAS environment by prescribing the airspace, airport locations and layouts, and weather conditions. The Infrastructure models are comprised of the remaining components that operate between two Agents or between an Agent and the Environment.

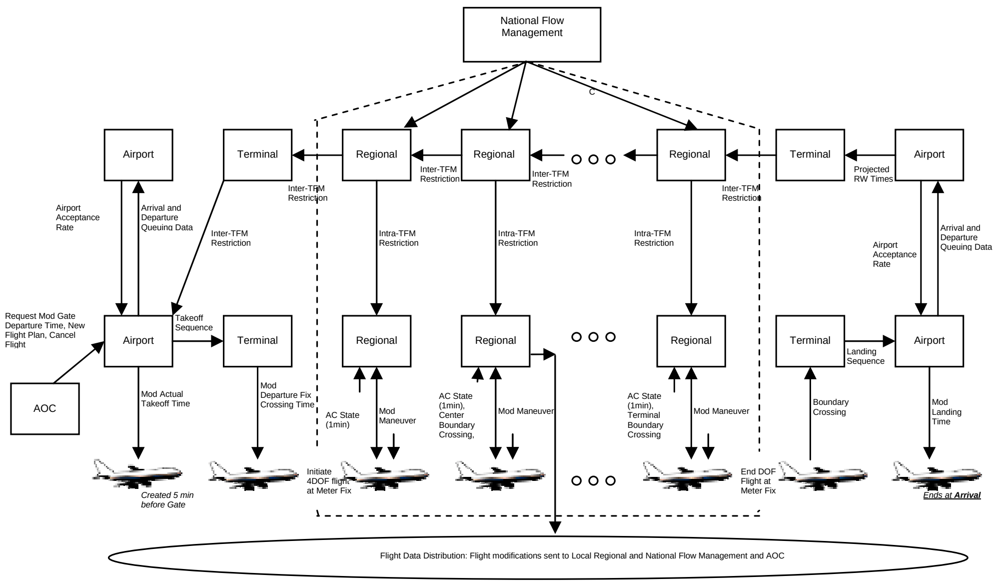


Figure 69: ACES Gate-to-gate Message Flow Between Agents [Source: Raytheon (2005, Appendix A)]

ACES can simulate various scenarios of the NAS due to its highly customizable input data. The input data includes specifications and data sets for the airport, airspace, aircraft performance, and flight demand. Since ACES is a capacity-based simulation model, the specifications for the airport (e.g., airport capacity, airport Traffic Flow Management, and airport taxi-in/taxi-out times) and the airspace (e.g., ARTCC latitude/longitude coordinates and sector maximum/minimum altitude) are the most detailed. Aircraft performance inputs specify the aerodynamics, weights, propulsion, control systems, and takeoff/landing capabilities of the aircraft. Flight demand input is the Flight Data Set, which is constructed from the ETMS scheduled flight data, nominal taxi time data, and nominal TRACON flight time data. Other input data are specifications for Surface Traffic Limits, Conflict Detection &

Resolution, Advanced Airspace Concepts, ACES grip map, scenario settings, and tail tracking pre-processor (Raytheon ACES team, 2005).

A.5 Jet:Wise

Jet:Wise (Niedringhaus, 2000, 2004), is an agent-based model created at the MITRE Corporation. This model explores a NAS marketplace emphasizing the airline operations. To imitate the interactions between the airlines, the NAS infrastructure, and the consumers, Jet:Wise models the economic decisions such as hubs location, fleet selection, scheduling, pricing, and airline reactions (to delays, congestions, and missed connections). It also addresses how airlines' decision-making is influenced by capacity-related events such as allowable airport hourly capacities, weather disruptions, and congestion delays. Jet:Wise simulates iterative cycles of the same virtual day rather than progressively over a simulation timeline. Using information from the previous cycles, the model learns to improve itself until the internal objective function is satisfied.

Jet:Wise models the CONUS as a collection of 191 Metropolitan Areas. Each cycle in Jet:Wise consists of the MARKET, FLY, and LEARN modes. In the MARKET mode, the model generates flight demand (i.e. passengers) based on a weighted average function of population sizes, incomes, and airport capacities. For each flight demand generated, there are multiple flight options to choose from. The model computes a weighted average "attractiveness function" for each flight option based on the fare, duration, range, airport capacity, distance to airport, airline's reputation and convenience of departure time. The passenger then selects a flight option through a logit model using these attractiveness functions. Once a flight option is selected, the initial flight demand now has a complete itinerary.

In the FLY mode, Jet:Wise simulates the mechanical flying of the completed itineraries. It does not account for en route position, air traffic control, or weather delays. An aircraft simply takes off from the origin airport and appear at the destination airport after a predetermined time. Should there be no runways to takeoff from or land into, the aircraft gets into a First-In First-Out queue that may result in a delay. Evidently, some flight demands will be unfulfilled at the end of the simulation day due to delays. Jet:Wise treats this loss of goodwill by forfeiting a percentage of the fares from these delayed flights.

In the LEARN mode, airline agents make economic decisions as profit-maximization entities and act as the primary constituents of the Jet:Wise model. These deliberative agents use past experiences to continually adapt to the changing environment and make more profitable decisions in the forthcoming iterations. The learning in the model can be continuous and discontinuous. Continuous tools learn from real-valued parameters such as fares and fraction of reserved seats. After series of iterations, optimal conditions for these parameters are achieved when maximum profitability is achieved. Discontinuous tools learn from discrete parameters such as buy/sell aircraft and create/cancel routes. Unlike continuous learning where the outcome of the learning can be observed immediately, the outcome of discontinuous learning may only show up a few cycles later. The interactions between these learning agents in creating a competitive environment allow Jet:Wise to successfully demonstrate the emergence of the hub-and-spokes network formation following the airlines deregulation in the 1970s.

A.6 Monte Carlo Air Taxi Simulator (MCATS)

MCATS (RTI International, 2006; Toniolo and Brindel, 2005), is a Monte Carlo Simulation (MCS) model created by RTI International with the emphasis on modeling potential regional air taxi networks and improving NASA's understanding of service providers' cost structures. The model has since been extended to include other SATS-like services such as fractional ownership and self-piloted lease. The primary purpose of the model is to analyze the business strategies for these air service providers by determining both the internal and industry-wide cost drivers. By measuring the financial performance of service providers, the impacts of technological and operational innovations are captured in the form of economic metrics. MCATS is developed as a Microsoft Windows-based application to allow for easy access and use.

MCATS can be divided into four main functional components: input, analysis, visualization, and output. The input component specifies the parameters for the desired scenario study, which includes simulator/analysis options (e.g., operational mode, simulation length, and number of MCS runs), airport information (airport list with customizable configuration for each airport), aircraft information (customizable aircraft properties, fleet distribution, and initial distribution to airports), passenger information (e.g., passenger volume, new trip request daily, and O-D statistics), service provider cost information (operational costs, pilot related costs, insurance related costs, and inventory related costs), and weather parameters (general weather, Meteorological Aerodrome Report weather, and Regional Climate Model weather). The analysis component implements the air taxi service dispatch logic, which includes functionalities for aircraft selection, deadheading strategy, delayed flights, aircraft hold patterns, weather effects, and pilot operations. The visualization component simulates a two-dimensional animation for the analysis runs either in real time or fast time. Lastly, the output component reports six categories of data: profit margin/ticket price, airport related data (e.g., number of aircraft arrivals/departure, average number of passengers per flight, number of passenger trips denied), aircraft related data (e.g., total distance traveled, total time traveled, airborne passengers per trip), passenger related data (e.g., total passenger distance/time traveled, trip time/distance statistics), costing related data (e.g., weekly cash flow statistics, cost element statistics, and cost element distribution), and pilot data (e.g., hours flown, assigned airport, assigned aircraft).

A.7 Aviation Databases

Air transportation researchers have always been meticulous in selecting and using data sets that would enhance the capability and/or validity of their models. Hence, the literature review starts by identifying the databases that are most commonly used to forecast air travel demand and to model the NAS infrastructure. The later sections of this chapter will mention these databases without providing specifics.

Both demand-centric and supply-centric models share a very similar list of referenced databases. This is expected since there is an apparent overlap in using aviation demand databases and NAS infrastructure databases for constructing models and for validation purposes. The FAA is the primary authority in acquiring aviation demand data starting with the Enhanced Traffic Management System (ETMS) Count data, which records flight information for each specific flight such as the airline, equipment type, origin and destination airports, and scheduled gate departure time, to name a few. The Aircraft Situation Display to Industry (ADSI) data is a commercialized variation of the ETMS data that filters out all military flights. The FAA also produces the Terminal Area Forecast (TAF) model, which projects enplanements and operations forecast within the NAS through year 2025. Besides that, a global company named Official Airline Guide (OAG) produces highly customizable commercialized databases of scheduled flights for different locations worldwide. Emphasizing the passenger demand profile, the United States Bureau of Transportation Statistics (BTS) conducts the Airline Origin and Destination Survey (DB1B), which is a ten percent sampling of airline tickets reported by air carriers, containing not only the flight schedule information but also itinerary details (most notably fares) of the passengers transported. However, Yang et al. (2008) has reported that significant amount of errors are present in this database and that many inputs are inconclusive due to lack of travel time information and consistency in recording the trip break points for multi-coupon trips. Nonetheless, the DB1B database remained the most reliable true O-D demand data source available at least at the aggregated level and they further pre-processed DB1B to retrieve the more accurate symmetric DB1B (sDB1B) database.

The NAS infrastructure databases measure the NAS conditions in the forms of aircraft performance, airline performance (e.g., on-time arrivals, financials, and delays), airport performance (e.g., efficiency and capacity), and weather conditions. The Eurocontrol Basic Aircraft DAta (BADA) model is an aircraft trajectory simulation model that is frequently used for defining aircraft performance. The BTS provides the Airline On-Time Performance and the Form 41 Schedule T-100 air carrier statistics data, which record monthly on-time performance data by certificated U.S. carriers. Certain subsets of Form 41 also report air carriers' financial statements. The FAA provides the Operations Network (OPSNET) data, which records the aggregated air traffic delays in the NAS. It also provides the Aviation System Performance Metrics (ASPM) data and the National Flight Data Center (NFDC) data, which re-cords information on airport efficiency (e.g., taxi-in and taxi-out) and airport location/capacity respectively. Finally, the Rapid Update Cycle (RUC) forecast by the National Oceanic and Atmospheric Administration (NOAA) provides frequently updated short-range weather forecasts that are well-suited for the domestic aviation community.

The last and perhaps one of the most important databases is the database of transportation activities. The most conclusive database for constructing and validating transportation activities to date is the 1995 American Travel Survey (ATS) commissioned by the BTS, which collected data for over half a million person trips from 163 Metropolitan Statistical Areas (MSA) within the CONUS U.S. Department of Transportation (1999). Not only does this database reports the travel volume between any two MSAs, it also provides the counts for each transport mode selected for this market, known as modal splits hereafter.

While this database is reliable when used to extract aggregated travel data, closer scrutiny of this database at the individual O-D level revealed numerous errors and data anomalies that cannot be neglected. One of the data anomalies involves large volumes of transportation activities defying the physical boundaries of specific regions. For example, the 1995 ATS reported 26,062 air trips of 750 to 800 miles internally within the Atlanta metropolitan, whereas the maximum trip distance within the state of Georgia is no more than 500 miles. Another form of undisputed data anomaly is observed in the total produced and attracted trips for certain MSA's. For example, the 1995 ATS reported exorbitantly large volume of trips produced by and attracted to the non-MSA locale in the state of Wisconsin and Michigan, which has neither the population size nor attractiveness to generate or draw such high volume of long distance trips. These two locales are eventually ranked twelfth and thirteenth overall ahead of inarguably more populated and attractive locales such as Boston, MA and Washington, DC. Meanwhile, the New York City, NY MSA is ranked sixth overall with only slightly more than half the first ranked non-MSA Texas locale, which in itself is seemingly dubious. Lastly, drastic differences are observed in the modal splits between the two directional traffic flows for the same market pair, inherently claiming that trip distance has insignificant influence on transportation mode choices for those market pairs.

One of the ways to reduce the severity of the data anomalies is by offsetting unsystematic and human-derived errors for specific data entries through aggregation. This aggregation can be achieved in many different ways, one of which is by assuming that the O-D matrix is diagonally symmetric. Hence, the total traffic flow (V_{ij}) rather than the two directional traffic flows (v_{ij} and v_{ji}) is used for describing each market pair, as shown in Figure 70. The justification for this assumption is that in studying the aviation SoS, we wish to analyze the overall performance of the market pairs (strength of the links) rather than performance of inbound versus outbound flights.

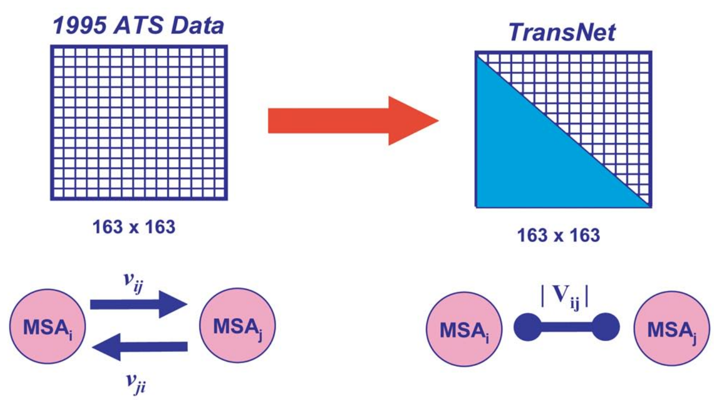


Figure 70: Data Processing for Calibration

APPENDIX B

AGENT-BASED MODELING & SIMULATION

The acknowledgement of the aviation SoS as a complex SoS calls for the adoption of a modeling approach capable of capturing the highly interactive and cognitive system behaviors. The agent-based modeling (ABM) technique is one such approach that is well-suited for modeling complex nonlinear dynamic systems. A brief historical account is first provided, leading into the elaboration on the operating mechanics behind the ABM technique. The extension of the ABM technique to a Multi-Agent System (MAS) is introduced, followed by the overall goals of the technique. Lastly, a discussion on the concept of emergence is provided, dwelling into how the ABM technique is well-suited for capturing emergence.

B.1 Historical Account

Several literatures have provided a good historical overview of the ABM technique (Epstein and Axtell, 1996). The earliest conceptualization of the ABM technique is credited to von Neumann's theoretical device for automata reproduction (1966). This device was improved with the help of Ulam and in turn materialized as a cellular automata device. The next big step was carved by Conway (1970), who constructed a two-dimensional virtual environment based on simple rules which he called the *Game of Life*. This technique was then heavily influenced by Rumelhart and McClelland

(1986) in the field of complexity science and by Reynolds (1987), Gasser and Huhn (1989), Holland (1992), and Langton (1992) in the field of artificial intelligence.

B.2 Operating Mechanics

According to Bonabeau (2002), ABM is a mindset that describes a "system from the perspective of its constituent units", which are represented by "autonomous decision-making entities called agents". Also known as individual-based model, the goal of the modeling technique is to capture the global consequences of a complex system *bottom-up* from the local interactions between constituting members of the system's population (Reynolds, 1999). The ABM technique is comprised of three main building blocks: agents, environment, and interactions.

Agents

While there are many different definitions for agents, an agent can be simply viewed as an independent entity that perceives the environment based on an evolving information bank and acts based on a predefined set of rules. Lewe (2005) pointed out that the two keywords that ultimately describe agents are *adaptiveness* (defined as the agents' ability to continuously adapt to the changing environment through past experiences) and *autonomy* (defined as the agents' ability to independently operate and react without external interventions). Ilachinski (1997, Chap. 1) provided an in-depth characterization of *adaptive autonomous agents*:

- It is an entity that, by sensing and acting upon its environment, tries to fulfill a set of goals in a complex, dynamic environment.
- It can sense the environment through its sensors and act on the environment through its actuators.
- It has an internal information processing and decision-making capability.
- Its anticipation of future states and possibilities, based on internal models (which are often

incomplete and/or incorrect), often significantly alters the aggregate behavior of the system of which an agent is part.

- An agent's goals can take on diverse forms: desired local states, desired end goals, selective rewards to be maximized, and internal needs (or motivation) that need to be kept within desired bounds.

Environment

Odell et al. (2002) stated that "an environment provides the conditions under which an entity (agent or object) exists " and is comprised of all agents, all non-agent entities, as well as the principles and processes that allows agents to exist and communicate. Tankelevich (2006, Chap.2), in the study of intelligent agents, further defined five conditions that characterize the environment:

- Accessible versus inaccessible: Accessible if sensors can detect all aspects of environment that are relevant to decision-making.
- Deterministic versus non-deterministic: Deterministic if next state of world is completely determined by current state and action selected.
- Episodic versus non-episodic: Experience is divided into episodes, where subsequent episodes do not depend on previous episodes.
- Static versus dynamic: Dynamic if environment can change while agent is deliberating. Static when agent does not worry about passage of time.
- Discrete versus continuous: Limited number of distinct, clearly defined percepts considered discrete.

Interactions

Having provided the definitions and descriptions for agents and environment, the mechanics behind the ABM technique can be discussed with the help of Figure 71. The fundamentals of the mechanics revolve around the *agent-environment interactions*.

As mentioned earlier, an agent possesses an information bank that contains information and knowledge pertaining the environment. An agent also has a set of desires and goals. In order to satisfy those goals, the agent makes a decision to undertake a specific action based on its goals and the known information. While the impact of one action is small, the aggregated actions of all agents within in the environment creates sufficient momentum to perturb the environment such that a new state of the environment is conceived. In turn, this perturbation is measured by each agent's internal memory and the information bank is updated to reflect the new state of the environment.

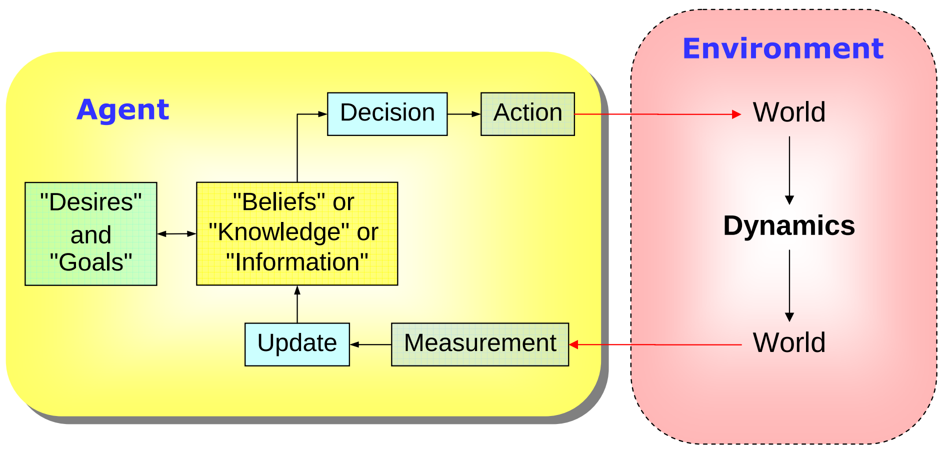


Figure 71: Agent-Based Modeling Operating Mechanics [Source: Lewe (2005, p. 34)]

The interactions between an agent and the environment facilitate the platform for the agent to adapt to the changing environment in order to achieve its pre-set goals. The level of sophistication of the agent's reasoning determines whether it is *reactive* or *deliberative*. Stone and Veloso (1997) defined reactive agents as agents that rely solely on the predetermined behaviors in a reflexive manner without possessing any internal state. On the other hand, deliberative agents learn to think by exploring through a space of behaviors while maintaining internal state. While there is no clear line to distinguish between these two types of agents, "an agent with no internal state is certainly reactive, and one which bases its actions on the predicted actions of other agents is deliberative." Here, an internal state is likened to an internal model or recapitulation of the world within an agent. Goodwin (1993) further stated four properties that "characterize the accuracy and suitability of the model for the task and how well the agent uses its model", as shown in Table 25.

Table 25: Deliberative Agents' Properties

Property	Description
Predictive	An agent is predictive if its model of how the world works is sufficiently accurate to allow it to correctly predict how it can and cannot achieve the task
Interpretive	An agent is interpretive if can correctly interpret its sensor readings
Rational	An agent is rational if it chooses to perform commands that it predicts will achieve its task
Sound	An agent is sound if it is predictive, interpretive and rational

B.3 Multi-Agent Systems

A Multi-Agent System (MAS) is an extension of the single-agent system where several interacting agents are present in the environment. Durfee and Rosenschein (1994) pointed out that a MAS problem typically focuses on how agents with individual goals and constraints will interact in a given environment such that each agent will act and compromise accordingly towards the attainment of a collective goal. Lewe (2005) documented a good description pertaining the different ways that a MAS can exist, particularly in terms of the interdependencies and the group dynamics between agents. Configurations of the different MAS architectures are shown in Figure 72.

From a single-agent's perspective, the biggest difference between a MAS from a single-agent system is that multiple agents are collectively in control of the environment's dynamics. While this would capture the dynamics in a realistic complex system, it also adds tremendous uncertainty and unpredictability to the problem (Stone and Veloso, 1997). Hence, careful considerations must be applied when declaring the agent and environment definitions for a MAS problem.

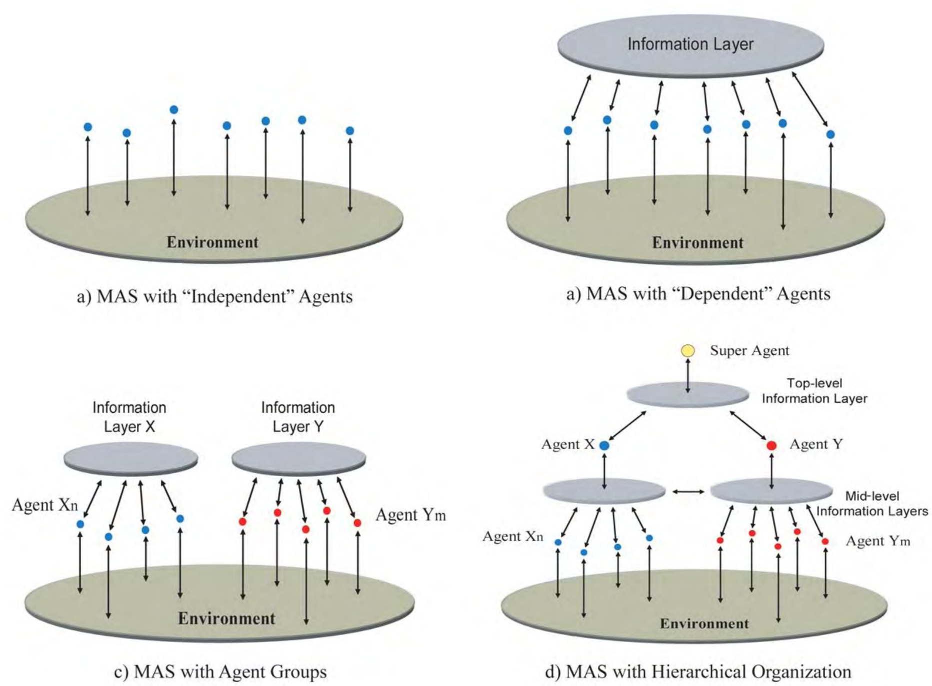


Figure 72: Different Multi-Agent System Configurations [Source: Lewe (2005, p. 36-38)]

B.4 Goals of ABM

Over the years, the ABM technique has been meticulously improved by and applied to various fields of study; mathematics, cybernetics, artificial intelligence, computer modeling, biology, economics, sociology, and political science to name a few. Part of the reason for this widespread popularity is because the ABM technique is highly flexible in serving the different purposes and goals of a broad spectrum of complex system studies.

Axelrod and Tesfatsion (2006) postulated that there are four forms of goals that should be pursued by ABM researchers: empirical, normative, heuristic, and methodological. Under the empirical goal, researchers seek to understand the true explanations behind the repeated interactions of agents in a given environment, which then dictate the types of observed global regularities generated by the model. Under the normative goal, researchers seek to determine if proposed design for the investigated systems will result in the attainment of desirable system performance over time. Under the heuristic goal, researchers seek to attain greater and oftentimes emergent, non-intuitive insights about the fundamental causal mechanisms in the system. Lastly, under the methodological goal, researchers seek to discover the best combination of methods and tools that will yield the most accurate and coherent outcomes when compared with real-world observations.

B.5 Emergence

One of the primary outcomes of these aggregated agent-environment interactions is the phenomenon of emergence. There are really no complete definition for emergence, as it is one of the naturally aspired phenomenon that is observed from living systems in various fields of study. However, one can loosely describe emergence by the phrase *the whole is somehow different from the sum of the parts.* From a reductionist perspective, emergence can be described as the outcome of non-linear interactions between large number of agent entities, where the rules operating at one level can cause unpredictable outcomes or rules to emerge at a higher level (Morowitz, 2002). In this sense, living systems emerge strictly from the bottom up, from a population of much simpler systems; instigating the belief that "complex behavior need not have complex roots (Waldrop, 1992)." Hence, the ABM technique is well-suited for modeling complex systems where emergence is a topic of interest. Morowitz (2002) further pointed out that emergences occur both in the model systems and in the real world. With a well chosen model, the researcher can hope to map the two kinds of emergences where they would resonate with each other.

APPENDIX C

NETWORK MODELING

Modeling techniques that employ network theory can be used to represent transportation systems as networks of origin and destination nodes connected via transportation links. The analysis framework of these networks is facilitated by the study of graph theory. Therefore, a brief introduction of graph theoretic concepts and its key indices is provided before the network modeling concepts are discussed.

C.1 Introduction to Graph Theory

Graph theory is the study graphs or mathematical structures that model the relationships between objects with commonalities. A *graph* is a set of *vertices* connected by *edges*, denoted as $G = (V, E)$ (Diestal, 2005). Any two vertices are *adjacent* if they share a common or *incident* edge. A graph can be directed or undirected. A directed graph is a graph where each edge has a numerical value that provide distinct definition and order for the edge. Meanwhile, an undirected graph is a graph where the edges are unordered and do not have distinctive numerical values. A mixed graph is a graph that has both directed and undirected edges. A *subgraph* $G' = (V', E')$ is an independent subset of a larger graph system, $G = (V, E)$, where $V' \subseteq V$ and $E' \subseteq E$. The *neighborhood* of a vertex is the subgraph that consists of all vertices adjacent to the vertex (and the vertex itself) as well as all incident edges between any two vertices in that subgraph.

A *walk* is an uninterrupted sequence of alternating vertices and edges where each edge is incident to a pair of preceding and succeeding vertices that make up the sequence. A *path* is a walk where there are no repeated vertices while a *trail* is a walk where there are no repeated edges. A *closed walk* is a walk where the initial vertex is the same as the terminal vertex. A *cycle* is a closed trail (with no repeated edges) and the only allowable repeated vertex is for the initial vertex to be the terminal vertex. The *length* of a walk is the number of edges traversed in the walk sequence. The *distance* between two vertices is the minimum length of any path between the two vertices. Meanwhile, the *eccentricity* of a given vertex v is the greatest distance between v and any other vertex in the graph. The minimum and maximum values of eccentricity for vertex v is referred to as the *radius* and *diameter* respectively.

Having briefly described the fundamental construct and measures of graph theory, several extended concepts of graphs are provided. One of the main concepts of graphs is connectivity, from which various indices and properties are defined. The connectivity of a single node is measured by its *order degree*, which counts the total number of edges that are incident to that given node. The order degree of a node, k, is comprised of in-degrees and out-degrees, representing incoming and outgoing edges respectively. The order degree measures the importance of a given node, where hub nodes have high order degrees and terminal nodes may have order degree as low as 1. A complete graph is a fully-connected graph where every distinct vertex pair is connected. A complete graph will have a total of $\frac{n}{(n-1)/2}$ edges and all vertices will have an order degree of $n-1$, where n is the number of vertices. A complete subgraph, also known as a *clique*, is then a subset of vertices within the graph that is fully-connected. A 9-node sample graph system shown in Figure 73 is used to depict the aforementioned graph properties. There are multiple cliques in the sample graph system: (2,4,5), (3,4,7),(3,4,6), (3,6,7), (4,6,7), and (3,4,6,7). A *maximal clique* is a clique (or multiple cliques) with the greatest connectivity from the set of all cliques in a graph. The maximal clique for the sample graph system is (3,4,6,7) with a size of 4.

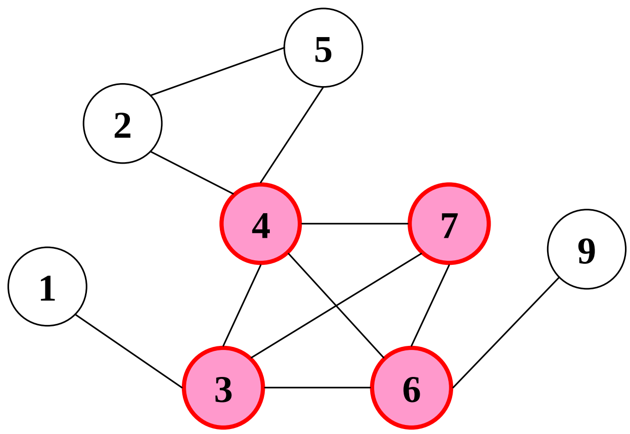


Figure 73: Sample Graph System

C.2 Transportation Network Modeling

The two constituents of networks are nodes and links. A node is a unique entity that is also a member of a larger system of entities. A link represents the flow between two nodes. A network is then a framework of links within a collective system of nodes. The arrangement and connectivity of this framework of linked nodes define the topology for the network. Network topology can be categorized into three main structures: centralized, decentralized, and distributed (Blum and Dudley). Graphical depiction of these structures are shown in Figure 74. Besides that, network structures can also be centrifugal or centripetal. A centrifugal network has a grid pattern and does not possess a center point since no one node stands out in terms of level of connectivity. A centripetal network has a converging pattern and possesses at least one center point since one or several nodes are much more connected that the others.

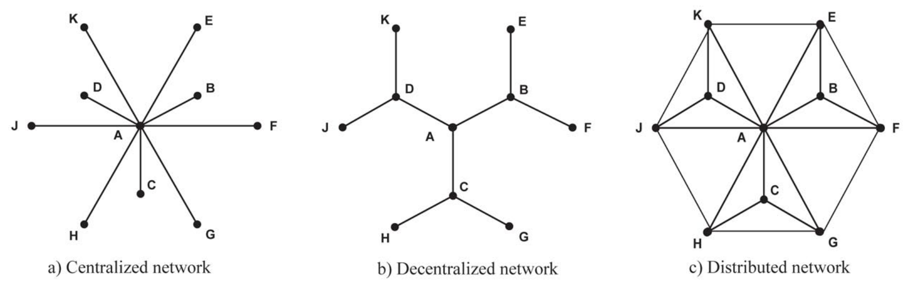


Figure 74: Network Topology Structures [Source: Blum (2001, p. 68)]

The representation of networks as graphs provides a tangible way of comparing networks and measuring the efficiency of networks through graph theoretic indices, where nodes and links are represented as vertices and edges respectively. Many of the fundamental graph theoretic indices were initially developed by Kansky (1963). As the network problem becomes more complex, network modeling concepts utilizing these graph theoretic indices and properties have also been expanded into more specific measures to better define the structural and quantitative properties of these network systems. Some of the key concepts are discussed next.

As the name intuitively suggests, *clustering coefficient* measures how clustered or connected the neighborhood of a vertex is. More specifically, clustering coefficient is a measure of the proximity of the neighborhood of a vertex from being a clique (Watts and Strogatz, 1998). The clustering coefficient of a directed graph e_{ij} is given as:

$$C_i = \frac{|e_{jk}|}{k_i(k_i - 1)} : v_j, v_k \in N_{i,e_{jk}} \in E \tag{23}$$

where $k_i =$ order degree of vertex v_i

For undirected graphs where $e_{ij} = e_{ji}$, the clustering coefficient is given as:

$$C_i = \frac{2|e_{jk}|}{k_i(k_i - 1)} : v_j, v_k \in N_{i,e_{jk}} \in E \tag{24}$$

$$\text{where } k_i = \text{ order degree of vertex } v_i$$

Network density measures how well developed a network is by taking the ratio of the number of edges (L) to the maximum possible number of edges (S) in the network. Network density along with clustering coefficient are two of the most commonly used indices for identifying network concentration at *hub* nodes. This concept is an ideal representation of hubs in transportation networks.

Besides connectivity, the length of a path in the network system is also of great interest particularly in transportation research. The length of a path is likened to the cost of having to traverse along a given path in the network and thus, the determination of the shortest path is most desirable. The gist behind the *shortest path method* is to locate the path between two nodes where the cumulative (weighted or unweighted) cost of the constituting edges for the path is minimal. Unweighted cost function can be viewed as counting the number of steps required for moving from the origin to the destination node. Weighted cost functions are oftentimes derived based on real-world cost metrics such as distance traversed (for transportation network problems) and network latency (computer network problem). Depending on the properties of the network, many algorithms have been conceived for solving the shortest path problem such as the Dijkstra's algorithm (Dijkstra, 1959) and the Moore-Bellman-Ford algorithm (Bellmann, 1958; Ford, 1956; Moore, 1959).

Several other key indices are listed below, where v = number of vertices and e = number of edges (Rodrigue et al., 2006):

- Pi Index (π) measures the relationship between the total length of the graph *L(G)* and the distance along its diameter *D(d)* as an indicator of the shape of the network. A high index indicates a more developed network

$$\pi = L(G)/D(d)$$

- Eta Index (η) measures the average length per edge, which goes down with the addition of vertices.

$$\eta = L(G)/e$$

- Theta Index (θ) measures the function of a node, that is the average amount of traffic per intersection. A high index indicate a high amount of load.

$$\theta = Q(G)/v \text{ where } Q(G) = \text{total flow}$$

- Beta Index (β) measures the level of connectivity in a graph and is expressed by the relationship between the number of edges over the number of vertices. A high index indicates a high number of possible paths.

$$\beta = e/v$$

- Alpha Index (α) measures the network connectivity by evaluating the number of cycles in a graph in comparison with the maximum number of cycles. Alpha have a value between 0 and 1 where 1 indicates a completely connected network.

$$\alpha = u/(2v - 5)$$

- Gamma Index (γ) measure the network connectivity by considering the relationship between the number of observed edges and the number of possible edges. Gamma is between 0 and 1 where 1 indicates a completely connected network.

$$\gamma = e/[3(v - 2)]$$

APPENDIX D

REVENUE MANAGEMENT SYSTEM

The theoretical foundation for the Revenue Management System and seat inventory control methods are explored in this section.

D.1 RMS: Core Concepts

The Deregulation of the airline industry in 1978 allowed for extensive use of computerized systems for selective pricing, such that empty seats in an aircraft can be discriminatively sold to higher paying customers. The conceptualization of Revenue Management System (RMS) was made in the early 1980s, often credited to airline executive Robert Crandall from American Airlines, as a retaliation strategy to the rapid rise of the discount airline People's Express (McAfee and te Velde, 2004). Since then, RMS has been widely used throughout the airline industry due to its high revenue returns. RMS has been attributed for generating US$500 million in additional revenue per year for American Airlines (Davis, 1994).

Cross (1997)postulated seven core concepts that drives RMS:

1. Use price to balance demand and supply
   - Focus on price rather than cost when there is an imbalance in demand and supply
   - Address short-term fluctuations first with price, then with capacity

2. Use market-based pricing
   - Reduce cost if necessary, but do not be confined to cost-based pricing
   - Exploit the market condition by setting prices that the customers will accept in a price-flexible environment
3. Use segment pricing
   - Pricing for the mass market results in loss of potential revenues
   - Vary prices to meet the price sensitivity of each market segment to maximize revenue and stay competitive
4. Favor the most valuable customers
   - Rather than using a first-in-first-out approach, save your products for the most valuable customers, that is, the highest-paying customers
   - Understand demand at the micromarket as accurately as possible and target the most valuable customers
5. Forecast at the micromarket level
   - Make decisions based on knowledge, not supposition
   - Gain knowledge of subtle changes in consumer behavior patterns
6. Exploit each product's value cycle
   - Based on previous concept, divide the market into submarkets that place different values on the product
   - Understand the value cycle and then optimally time the availability and price of the product to each micromarket segment
7. Continually reevaluate revenue opportunities
   - Provide updated information to top management to ensure the best top level decisions can be made
   - Provide decision-support tools to the workers to make dynamic decisions at the micro-market level

D.2 RMS: Seat Inventory Control Methods

Belobaba (1987) defined seat inventory control as "the practice of balancing the number of discount and full-fare reservations accepted for a flight so as to maximize total passenger revenues and/or load factors." *Balancing* is a keyword in this definition because *revenues* and *load factors* are conflicting objective functions governed by price, especially when fare levels are heavily influenced by price competition in the same city-pair market. Excessive full-fare pricing leads to loss of market shares and subsequently lower load factors while excessive discounted-fare pricing brings about higher load factor but dilutes the per-passenger revenues.

In general, the goal of RMS is to increase revenue not only by selling all possible seats in an aircraft, but also by selling them at the highest possible expected return. Some of the earliest reference to RMS methods was done by Beckman (1958), Thompson (1961), and Taylor (1962). Being airline employees, they recognized the need and value of selling more aircraft seats than available capacity in anticipation of *no-shows* (Chatwin, 1999). Today, this practice is referred to as *overbooking* in the airline industry. However, some may argue that overbooking in itself is a business strategy that precedes RMS but merely using the same control method popularized by RMS, that is, booking level/limit. Thus, the booking limit, protection level, and bid control methods are first reviewed, followed by the overbooking strategy. The Expected Marginal Seat Revenue (EMSR) model and Littlewood's reservation rule are then discussed.

Booking limit is a method that partitions the seats in an aircraft into different fare classes such that the sum of seats in every fixed-limit partition equals to the capacity of the aircraft. The general purpose of booking limit is to reserve a desirable number of seats for the higher-paying customers (Kimes, 1989; Laguna, 2004; Weatherford, 2003). In the case of a nested fare structure, the nested booking limits is

$$b_1 > b_2 > \ldots > b_n \tag{25}$$
$$b_1 = M, \text{ where M = capacity}$$

Protection level is an extension to the booking limit, where in a two fare class example, S_2^1 denotes the number of seats protected from class 2 but available exclusively to class 1. Here, the protection level for class 1 is simply the difference between the total capacity and the booking limit for class 2. In a more general problem, the protection level for the j^{th} class, Q_j, is the capacity saved for classes j, $j-1$, ..., 1:

$$Q_j = C - b_j \tag{26}$$
$$\text{where } j = 2, \ldots, n \qquad C = \text{capacity}$$

Bid price control is a revenue-based reservation control method where a request is continually accepted as long as the revenue gained from that request exceeds a threshold price, P_{thr}. This threshold price is typically a function of time and remaining capacity, and must be adjusted after every sale (Laguna, 2004). Despite being mathematically simple, this method has not been widely used in the airline industry because the underlying business processes changes too significantly and rapidly (Boyd, 2002).

Overbooking is a business strategy based that manipulates the booking limit method. This strategy is described by the act of airlines selling more seats than they have available in anticipation of no-shows from some of the customers who reserved seats. With overbooking, airlines can fill up more seats that risk being flown empty due to no-shows. The probability that a customer will cancel a previous order declines as the delivery date approaches (Chatwin, 1999; Laguna, 2004; Taylor, 1962).

An approach for overbooking is shown as follows (Bell, 2005):

$$B = \text{booking limit}$$

$$C = \text{capacity}$$

$$R_N = \text{value of sale of unit } N$$

$$T_i = \text{cost of satisfying } i^{th} \text{ overbooking}$$

$$P[Q|B] = \text{probability that } Q \text{ customers will show up to buy } B \text{ units}$$

Expected cost of unsold seats:

$$\sum\{(R_{Q+1} + R_{Q+2} + \ldots + R_C) \cdot P[Q|B]\} \text{ for all } Q < M \tag{27}$$

Expected cost of handling oversold customers:

$$\sum\{(T_1 + T_2 + \ldots + T_{Q-M}) \cdot P[Q|B]\} \text{for all } Q > M \tag{28}$$

Through the above model, the optimal booking limit is obtained when the sum of the two expected costs is minimized. The revenue gain from overbooking by achieving the optimal booking limit is graphically depicted in Figure 75 (Bell, 2005).

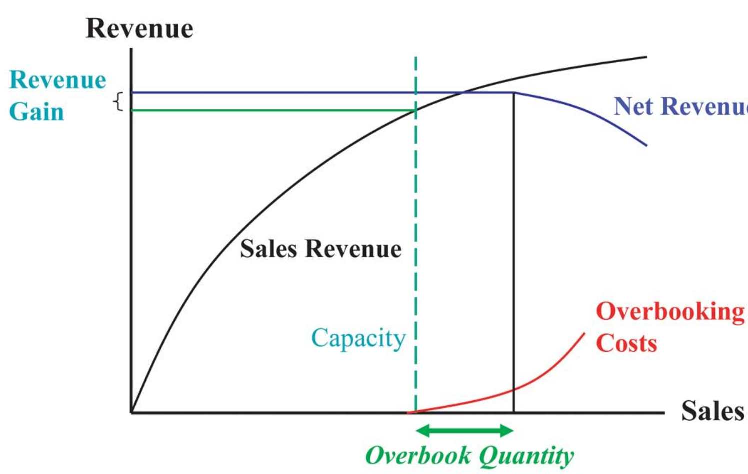


Figure 75: Optimal Level for Overbooking [Source: Bell (2005, p. 71)]

Littlewood (1972) demonstrated a dynamic reservation experiment for a single flight leg with two fare classes and arrived at the deduction of the Littlewood's *reservation rule*. This rule states that revenues could be maximized by prohibiting sales at the low fare price when the known revenue from the sale of another low fare seat is less than the expected revenue of saving that seat for a potential high fare customer. In other words, seats priced at the low fare should be sold continually as long as

$$f_{low} \geqslant [1 - P(S_{high})] f_{high} \tag{29}$$

Belobaba (1989) developed the *Expected Marginal Seat Revenue* (EMSR) model, which became the standard application of the aforementioned inventory control methods. He defined EMSR as the "expected marginal seat revenue for class i when the number of seats available to that class is increased by one", where the EMSR of the S_i^{th} seat in fare class i is then the product of the average fare in that class and the probability of selling S_i or more seats :

$$\begin{aligned} EMSR(S_i) =& P_i(S_i) \cdot f_i \\ \text{where } f_i =& \text{ average fare in fare class } i \\ S_i =& \text{ number of seats allocated to fare class } i \text{ made} \\ P(S_i) =& \text{ probability that the } S_i^{th} \text{ seat available to} \\ & \text{ class } i \text{ will be sold} \end{aligned} \tag{30}$$

To demonstrate Littlewood's reservation rule via the EMSR model, consider the aforementioned two fare class model with fare levels f_1 and f_2. Let the booking limit for class 1, BL_1, be the total available capacity of the aircraft, C. Let S_2^1 be the seats protected from class 2 and available exclusively to class 1. Then, the optimal protection level for class 1, S_2^{1*} is obtained when:

$$EMSR_1(S_2^{1*}) = f_2 \tag{31}$$

This optimal value can be graphically depicted as the intersection between the $EMSR_1(S_1)$ curve and f_2, where the booking limit for class 2 is shown as b_2. Evidently, the sum of S_2^{1*} and b_2 equals the C or b_1, as shown in Figure 76.

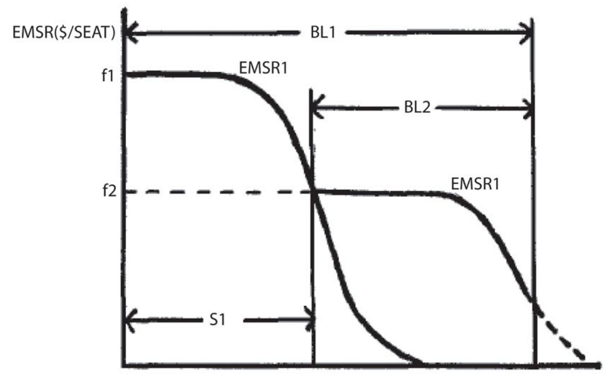


Figure 76: Optimal Protection Level for Revenue Maximization in a Two Fare EMSR Model [Source: Belobaba (1989, p.187)]

This model can be extended to a multiple fare class problem by simply making nested comparisons of expected marginal revenues among the relevant classes. For a single leg flight with k fare classes, the optimal protection level, S_j^i must then satisfy:

$$EMSR_i(S_j^{i*}) = f_j, \qquad i < j, \qquad j = 1, \ldots, k \tag{32}$$

The total number of comparisons required for a nested problem with k fare classes is $k(k-1)/2$. These protection levels are then used to compute the booking limits on each fare class j:

$$b_j = C - \sum_{i<j} S_j^i \tag{33}$$

The seat inventory control methods and the EMSR model discussed above provide the theoretical foundation for exercising the RMS method.

APPENDIX E

REINFORCEMENT LEARNING TECHNIQUE

E.1 Introduction to Machine Learning and Reinforcement Learning

Machine Learning started out as a subfield of artificial intelligence and has since grew into a prominent field of study by itself. Carbonell et al. (1983) defined machine learning as the "study and computer modeling of learning processes in their multiple manifestations, [which include] the acquisition of new declarative knowledge, the development of motor and cognitive skills through instruction or practice, the organization of new knowledge into general, effective representations, and the discovery of new facts and theories through observation and experimentation."

Contemplations on designing machines that learn versus machines that perform as desired in the first place may lead to the questioning of the purpose of Machine Learning. In response, Carbonell, Michalski, and Mitchell (1983) further pointed out that "understanding human learning well enough to reproduce aspects of that learning behavior in a computer system is, in itself, a worthy scientific goal." Nilsson (1996) further identified several key engineering reasons for creating machines capable of learning, as summarized below:

- Example-centric definitions are sometimes the best way to specify the relationships between inputs and outputs of a system. The learning machine can approximate these relationships by adjusting its internal structure.

- Important relationships and correlations may be hidden among large data sets. The learning machine can extract these relationships.
- Oftentimes, machines do not perform as desired in their operating environment since the human designer could not fully capture the characteristics of the operating environment. The learning machine can improve this environment definition.
- The amount of knowledge available and required for certain tasks may overwhelm the encoding of these knowledge. The learning machine can be designed to learn these knowledge gradually and may even capture more information than the human designer had intended.
- The learning machine can adapt to constant changes in the operating environment, reducing the need for redesign.
- New knowledge about certain tasks is constantly being discovered. The learning machine can be used to encapsulate new knowledge instead of having to constantly redesign the system.

In the midst of the rapid advancement of Machine Learning in the 1990s, Dietterich (1997) identified four key directions of the research: learning ensembles of classifier systems, scaling up supervised learning algorithms, reinforcement learning, and learning stochastic models. The emphasis for the remainder of this section will be on *Reinforcement Learning* (RL).

Machine Learning can be categorized into supervised learning and unsupervised learning. Simply put, supervised learning refers to learning with the supervision from an external source whereas unsupervised learning does not. For example, a neural network program written to down-select optimal actions for a manufacturing plant is a supervised learning machine since guidelines for handling processes under given conditions are explicitly provided. A simulation program that explores combinations of actions for the same manufacturing plant while learning to make positive actions through a trial-and-error process is an example of an unsupervised learning machine.

Based on these descriptions, Reinforcement Learning is an unsupervised learning algorithm since RL agents explore the environment and exploit reinforcements or rewards from the environment without any form of external supervision. *Making actions/decisions by trading off between exploration and exploitation for maximizing rewards* is the heart of the RL method.

The earliest reference to Reinforcement Learning was the checkers game program by Samuel (1959). Samuel (1959) went on to play a key role in defining the logical instruction sets of early IBM computers, paving the way for modern computers. Another famous work is the TD-GAMMON program developed by Tesauro (1992, 1995), which learnt to play backgammon well enough to test the best human players. Since then, RL has been applied to areas of study such as robot controls (Connell and Mahadevan, 1993), elevator scheduling (Crites and Barto, 1996), telecommunications channel allocation (Singh and Bertsekas, 1997), and airline dynamic pricing (Gosavi, 2004).

E.2 Basic Mechanics

Trial-and-error and delayed reward are the two most important characteristics of Reinforcement Learning, which give rise to the concept of exploration and exploitation. The goal of an RL agent is to maximize the reward received upon making an action. To do so, the agent prefers actions that it has attempted in the past and known to be effective actions, that is, exploitation of past knowledge. However, the agent has to try previously unattempted actions in order to find these effective actions, that is, exploration of actions. Exploitation and exploration have to be jointly pursued to achieve the task. Thus, the RL agent adopts both strategies and learns to progressively favor and select the best actions (Sutton and Barto, 1998).

An RL agent is connected to the environment through its perception and actions.

Thus, an RL model is comprised of three components: a discrete set of environment state (S), a discrete set of actions (A), and a set of scalar rewards (R). First, the agent receives and input indicating the current state of the environment s, where $s \in S$. Next, the agent chooses an action a, where $a \in A$. This action changes the state of the environment, which is communicated to the agent via a scalar reinforcing signal or simply reward r, where $r \in R$. To better understand this agent-environment interaction, the information flow and an intuitive example are provided in Figure 77 (Kaelbling et al., 1996).

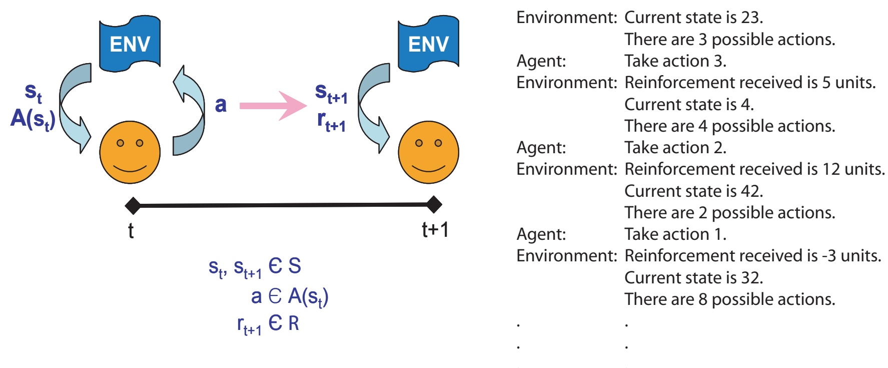


Figure 77: Reinforcement Learning Agent-Environment Interactions [Adapted from Kaelbling (1996)]

Having discussed the agent-environment interaction, the reinforcement learning mechanism is elaborated next. There are four main elements in an RL system: policy, reward function, value function, and model. A policy defines the agent's behavior by mapping from perceived states of the environment to the actions that should be taken under in those states. A reward function indicates the desirability of a given state by mapping each perceived state-action pair to a reward value. A value function indicates the long term desirability of states in consideration of previously encountered states. The reward function is usually given directly by the environment while the value function has to be constantly reevaluated by the agent over time. Lastly, the model replicates the behavior of the environment and is used for planning future actions through predictions of the resultant next state and next reward[1].

In summary, a policy tells the agent what to do based on the reward function. The reward function tells the agent what a good immediate action is and it is influenced by the value function. The value function tells the agent what a good long term game plan is based on the model of the environment. The model tells the agent how the environment looks like and facilitates predictions for the next set of estimates. The ultimate goal of RL is to determine states that yield the highest value (not the highest reward) by maximizing the long run total rewards. Approximating this value function is the core research focus for almost all RL problems. Some of the most widely used methods for approximating value functions are Monte Carlo methods, dynamic programming, Q-learning, advantage learning, and temporal difference. These methods are thoroughly discussed in (Eden et al.; Harmon and Harmon, 1996; Kaelbling et al., 1996; Sutton and Barto, 1998).

[1] While the model plays a significant role, it is not strictly required since RL systems can also be explored through explicit trial-and-error without having to *know* the environment.

APPENDIX F

AUXILIARY DATA

Table 26: Decile Income Distribution for MSA Locales, Base Year = 1999

	Decile Income Distribution									
MSAID	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
AKROH	16997	27080	35622	44002	52321	61713	72793	88139	115480	151356
ALBNY	17642	27613	36534	45283	54304	63707	75079	90162	116090	146625
ALBNM	13693	22198	30249	37764	46038	55172	66500	81950	108305	140808
ALLPA	18257	27493	35616	43677	52114	61309	71768	87181	112135	142595
ANNMI	23960	36221	47104	57549	67771	79369	93089	110653	142669	184439
APPWI	23367	32987	41409	49200	56180	63490	71994	84016	105537	133803
ATLGA	18575	29766	39749	49449	59313	70435	83710	102670	138208	184309
ATLNJ	17296	26399	34720	43085	51623	61225	72179	87171	112810	145102
AUGGA	12159	20740	28782	36832	45079	53684	64751	78882	103764	133376
AUSTX	18808	30016	39833	49495	59426	70163	83019	101375	136356	180601
BKRCA	10606	17342	24227	31262	39403	49008	60225	74658	99320	124021
BALMD	17872	29148	39287	49317	59324	70252	82999	100838	131818	170604
BTRLA	11941	21078	29597	38011	47078	57131	68469	83122	108551	138412
BEATX	11014	19687	27198	34854	42790	51660	62673	76972	100321	125476
BERNJ	21474	34061	46081	57588	70501	83997	101014	123362	169928	N/A
BGHNY	15313	23826	31117	38159	45698	53622	63837	77348	101978	128139
BIRAL	13321	22525	30902	39266	48078	57762	69452	85481	115987	156473
BSEID	17997	26392	33997	41578	49262	58158	68324	82678	107923	139770
BOSMA	20262	33275	45292	56695	68341	81314	96694	118148	162630	N/A
BLDCO	22825	35811	47637	58126	70163	83326	98775	119380	162216	N/A
BUFNY	14606	24275	32256	40637	49146	58326	69344	83454	107357	134796
CANOH	16730	25459	32442	39825	47169	55226	64582	77686	101455	130124
CHANC	13000	22141	30452	38305	46802	56013	66596	81216	107192	139755
CHAWV	13013	21251	28445	35971	43991	52229	62404	77159	102422	131683
CHLNC	17827	27743	36468	45158	53869	63427	75052	91568	122474	165172
CHTTN	14460	22850	30344	37626	45084	53351	62834	76955	102217	135793
CHIIL	17638	29723	40269	50616	61146	72491	86671	105897	143292	195695
CINOH	17396	28219	37437	46527	55612	65227	77206	93797	124894	168142
CLEOH	15926	25931	34820	43159	52047	61751	73094	88764	116470	152279
COSCO	20021	29532	38195	46166	53996	62937	74889	89548	117019	149351
COLSC	15559	25198	33587	42211	50955	60643	71647	86711	112540	146278
COLOH	17553	27851	36950	46027	55038	64722	76202	92192	120465	158601
CCTTX	10803	18310	25547	32852	40856	49311	60111	73688	96322	124210
DALTX	16987	27004	36295	46030	56364	67766	81957	101851	139321	190041
DAYOH	16600	26150	34314	42253	50964	60259	71049	85631	110370	139236
DAYFL	15236	22877	29175	35544	42126	50179	59054	71867	95850	126196
DENCO	21100	32065	41915	51523	61290	72018	84918	103143	137024	183286
DMEIA	20691	30713	39867	48333	56674	65480	76005	90465	117603	156748
DETMI	17040	28171	38360	48561	59205	70528	83820	101684	131909	170151
DCHNY	21682	34072	44602	53573	63255	74520	86384	103531	132645	164627
ELPTX	N/A	15487	21037	26822	33409	41254	50804	63678	87122	112307
ERIPA	15524	23378	30471	37568	44829	52498	61864	73923	94614	119581
SPROR	14585	23328	30788	37661	45111	53120	62965	76173	101041	131355
EVSIN	16362	25404	33415	41167	49207	57197	66908	79637	103072	131290
FYVNC	13193	21364	28529	35166	41458	49167	58134	70353	91221	115866
FLTMI	13671	23165	31590	40672	50090	60440	71985	87454	110153	135616
FLAFL	15441	24487	32352	41123	50531	60923	73292	91261	123046	165498
FMYFL	16935	25389	32015	39072	46430	55107	65515	80702	113861	160327
FWYIN	19319	28321	36459	44102	51831	60150	69713	82603	105695	132008
FWATX	17223	27227	35864	44397	53230	63580	75993	92766	121699	158385
FRSCA	10491	17361	24145	30966	38575	47431	58697	73612	100217	130225
GRYIN	15937	26187	35169	44144	52755	62290	72321	85799	108570	136237
GRAMI	19302	29369	37912	46141	54117	62558	72714	86271	111357	143204
GRBNC	16226	25295	33331	41261	49328	57788	68302	82939	109970	145240
GRVSC	14662	23090	30902	38481	46366	54819	65106	78808	104736	134586
HMTOH	20461	31054	39668	48312	57514	66811	78147	92988	117046	144256
HBGPA	18700	28118	36200	44056	51891	60953	70852	85233	108988	138253
HARCT	19532	31622	42496	53405	63933	74884	87860	105496	137360	177376
HICNC	16059	24092	30886	37656	44475	51708	59890	71062	92115	117310
HOUTX	14009	23294	31838	41066	51212	62587	76959	96389	130884	174188
HUNAL	15233	25286	34434	43026	52250	62808	75180	91663	117950	148037
INDIN	18324	28275	37198	46082	55192	64823	76440	92383	120338	156517
JSKMS	11520	20571	29246	37437	46356	56042	66864	82258	109311	145830
JSVFL	16008	25534	33544	41618	50189	59142	70189	85420	112967	149764

Unavailable data points are marked as N/A

Table 27: Decile Income Distribution for MSA Locales, Base Year = 1999 (Continued)

	Decile Income Distribution									
MSAID	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
JCYNJ	10794	19453	27450	35452	44053	54118	66641	84331	114580	148290
JHNTN	12368	19772	26056	32113	38720	45703	54535	66502	87596	114342
KZOMI	16406	25852	33937	41798	50495	59350	69632	83633	108088	136298
KCYKS	19275	29433	38192	46983	55778	65415	76693	92315	120481	157620
KNXTN	14513	22931	30621	38001	45697	54520	64651	78950	105979	138282
LKLFL	14285	21807	28293	34569	41442	49513	58623	71418	93440	122169
LCTPA	20402	30083	37986	45138	52514	60841	70039	82805	106596	135169
LSGMI	18347	28903	38041	46874	55699	65394	76514	91032	115322	144665
LASNV	16519	25167	32614	40517	48420	57073	68123	82966	109018	141931
LEXKY	14563	24013	32460	41003	49876	59643	70733	85540	113273	151923
LRKAR	14490	23414	31351	39037	46753	55337	65891	80346	105594	138813
LALCA	11908	20155	28056	36645	46452	58114	72209	92396	128907	177481
LOUKY	15379	24930	33086	41319	49774	58926	70153	85220	112845	148171
MACGA	11684	20853	29335	37788	46279	55303	65507	79716	102578	129464
MADWI	23841	36074	46025	55136	62966	71802	83346	98399	127113	166168
MALTX	0	11496	15757	20590	26009	32301	41038	53031	74618	99727
PBYFL	16694	25148	32363	39855	47572	56362	67000	81385	106047	135124
MEMTN	11804	21304	30095	38511	47441	57563	69234	84663	113415	153463
MIAFL	10625	17948	24839	31934	40260	49892	61436	78283	110575	154419
MSXNJ	27007	40954	52961	65124	77074	90216	106018	128854	170885	N/A
MILWI	17390	28608	38194	47635	56797	66505	77949	93088	120698	157376
MPSMN	24103	36214	46771	56156	65449	75499	87477	104079	136215	179500
MOBAL	10881	19188	27088	34728	42118	50849	60573	74080	97198	128097
MODCA	13104	20957	28800	36395	44703	53355	63656	77489	101384	129113
MTHNJ	21912	33422	44267	55135	65995	78245	93021	113718	152271	N/A
MONAL	12519	21674	29904	37474	45819	54621	64989	79454	105141	133786
NSHTN	16822	27371	36095	44706	52679	62130	73459	89151	119513	160742
NASNY	26346	40727	52833	64694	76430	89526	105000	127320	169665	N/A
NHVCT	17932	30024	40768	51655	62288	74073	87506	105678	140074	185156
NLNCT	20931	31075	40389	49280	57901	67710	78909	94475	121947	152857
NORLA	10109	18243	26182	34135	42647	52122	63906	79249	107093	142851
NYCNY	N/A	17340	26517	35893	46471	58936	74301	96411	137899	198571
NEWNJ	18250	31286	43425	55615	67886	81929	98990	122254	169271	N/A
NBHNY	18357	29806	39673	49275	58415	68798	81345	96768	122592	151529
NORVA	15850	25292	33153	40996	49187	57771	68181	81998	106253	134865
OAKCA	19973	32995	45032	56584	68902	82297	98710	120365	161913	N/A
OKLOK	13909	22436	30016	37176	45059	53687	64150	78265	102934	133017
OMHNE	19524	29533	38045	46369	54596	63679	74296	88917	115054	148870
OCTCA	20249	31345	41811	52603	64611	78110	94231	115492	156882	N/A
ORDFL	16251	25042	32406	40231	47760	56850	68058	83970	112819	149347
PENFL	12896	21476	28964	36049	43233	51532	61558	74468	99172	128124
PEOIL	17492	27191	35672	44151	52358	61279	71300	85443	108651	137014
PHIPA	16485	27795	37770	48011	58394	69687	82726	101048	134525	177786
PHOAZ	16799	25936	34181	42169	51126	61039	72929	89865	120284	160007
PITPA	15615	24178	31626	39464	47546	56541	67135	81550	108194	142349
POROR	19103	29573	38355	46872	55669	65303	76903	93054	122117	158827
PVDRI	14809	24772	34225	43015	52298	62189	73198	88252	114652	146917
PRVUT	17736	26882	34779	41974	50196	58235	68573	82864	107680	137521
RLGNC	18278	29572	39368	49474	59405	70285	83679	102322	134677	174978
RDGPA	18961	28486	36754	45026	52998	62010	72247	85767	108996	138153
RENNV	18666	27629	37069	45253	54284	63757	75232	91956	120827	162030
RCHVA	17877	28493	37603	47201	56309	66053	77902	94203	123629	161494
RVRCA	13694	22281	30457	38564	47400	57159	68829	84223	109631	138340
ROCNY	16914	27291	36163	44825	53610	62860	74315	88980	114534	145716
RFDIL	18195	28088	36745	44949	53424	61887	72070	85623	109408	140714
SACCA	16272	26629	35560	44508	54006	64870	77436	94466	122448	157101
SGNMI	15048	23978	31609	39959	48807	58543	70331	85519	109662	136470
SLSMO	17046	27525	36332	45151	54102	63660	75112	90844	119484	156353
SLMOR	15438	24911	32043	39591	47009	55261	65050	77396	99391	122926
SLNCA	16379	25766	34254	42264	51169	61455	75180	92690	122558	162746
SLCUT	20654	30582	38736	46514	54470	63312	74353	89254	115148	148043
SANTX	12993	21451	28982	36390	44729	53520	64566	79768	107283	139805
SDGCA	16184	25756	34463	43557	53438	64725	78300	97344	130341	172631
SFRCA	21822	35804	48534	61287	75219	91182	110480	139876	N/A	N/A
SJSCA	24940	40439	53758	67256	81717	97902	116454	143919	192386	N/A
SBRCA	17016	26910	35414	44465	54042	65586	79728	98565	135698	191044
SRSCA	21867	33079	42757	52327	61921	72788	86559	104709	137138	179748

Unavailable data points are marked as N/A

Table 28: Decile Income Distribution for MSA Locales, Base Year = 1999 (Continued)

	Decile Income Distribution									
MSAID	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
SARFL	17826	26082	33319	40833	48624	56908	68483	84967	118377	167621
SCRPA	14992	22573	29754	36495	43606	51486	60893	73457	95215	121091
SEAWA	21772	33626	43989	53771	63757	74498	87305	104908	138731	184440
SHRLA	10186	17382	24606	31985	40216	48801	59439	73386	98146	127734
SBDIN	16414	25779	33579	41321	49652	58053	68689	82610	106312	135298
SPKWA	15357	24089	31490	38558	46463	54755	64349	77730	101578	127898
SPRMO	15519	23209	29694	35901	42263	50221	59443	71668	95368	124642
SPRMA	13533	23521	32411	41655	50932	60380	70842	84796	108934	136177
STKCA	12784	21095	29460	37910	46920	56841	68585	83547	107972	136377
SYRNY	15477	24647	32763	40721	49271	58475	68991	83163	108087	136794
TACWA	17247	27096	35469	43535	52098	61216	71681	85472	108445	136149
TALFL	12678	22555	31743	41055	50086	59523	71226	86431	114083	149493
TMPFL	15529	23476	30590	37597	45353	54036	64965	80301	108780	145320
TOLOH	14713	24753	32717	41459	50286	59443	70241	84113	109601	140866
TRTNJ	20680	33252	45247	56578	68494	82349	99026	120713	164713	N/A
TUCAZ	13826	22074	29377	36473	44446	53226	64035	79289	106649	141808
TULOK	15021	23304	30920	38539	46480	55511	65957	80362	105861	139136
UTINY	13862	22161	29507	36592	44174	51741	60942	72990	93587	117658
VALCA	20523	31107	40955	50639	60754	71415	83743	99874	127583	160327
VTRCA	20954	32768	43345	53783	65286	77633	92331	111711	149368	193254
WASDC	23617	37106	49914	61611	73877	87470	103436	125939	166268	N/A
WPBFL	17317	26802	35591	44297	53701	65115	79657	101445	147731	N/A
WICKS	18159	27661	35863	43664	51661	60666	70480	83563	105332	132595
WMTDE	20754	31613	41984	51594	61245	71934	84373	100960	130549	164653
WCTMA	17494	28577	38776	49037	58741	69327	81798	98850	126159	158907
YRKPA	20479	29699	37319	45151	52278	60206	69117	81243	103208	128932
YTWOH	14647	22822	30110	36891	44111	52203	61964	74505	95235	117936

Unavailable data points are marked as N/A

Table 29: Decile Income Distribution for Non-MSA Locales, Base Year = 1999

	Income Distribution					
MSAID	0.1	0.3	0.5	0.7	0.9	0.975
NMTAL	14765	28143	42281	58865	105337	172029
NMTAR	13888	25192	36608	51471	96435	163908
NMTAZ	15719	30090	43978	60845	121135	223081
NMTCA	16773	31884	48108	69116	127564	207363
NMTCO	21003	40952	59111	79551	144960	231928
NMTCT	18983	35204	50595	70376	130028	215109
NMTDE	20225	37167	50945	68145	118096	188435
NMTFL	15396	28423	42277	60032	117171	199892
NMTGA	16345	30638	44014	60409	103793	158382
NMTIA	18503	34262	47311	60896	100291	155722
NMTID	17847	31146	41122	54681	100067	162923
NMTIL	18032	34576	50032	67473	123231	203876
NMTIN	18590	33349	46831	62449	118140	195217
NMTKS	18284	34602	48560	64959	119639	209125
NMTKY	14814	28460	40105	58192	112201	193766
NMTLA	13347	26041	39146	56814	101354	153334
NMTMA	19690	39104	58383	77757	144412	233108
NMTMD	21480	41221	60400	82574	154614	253923
NMTME	15975	29935	44575	59110	103785	164232
NMTMI	17927	34551	49481	67901	120629	200814
NMTMN	22608	41684	57413	73265	131460	223411
NMTMO	18482	33166	48140	62863	110613	176320
NMTMS	13456	25308	37162	53982	95406	145342
NMTMT	14788	27087	38329	51901	87230	135164
NMTNC	14884	28255	41448	57980	110180	183253
NMTND	16805	32589	43294	56596	94449	147519
NMTNE	19242	34756	49557	62889	107123	160862
NMTNH	23128	42582	58367	75372	137905	226178
NMTNJ	20391	40177	59929	82370	153362	268889
NMTNM	13748	25851	37369	52563	99254	157011
NMTNV	19143	32444	45463	61897	112445	180521
NMTNY	16076	32124	48531	69180	130431	216061
NMTOH	18216	33660	47692	65198	117277	195175
NMTOK	15483	29070	39654	54125	97680	150011
NMTOR	17367	31337	45293	60679	109712	175976
NMTPA	18548	34170	48543	66624	129371	223152
NMTSC	14957	29581	42682	60210	104378	157634
NMTSD	18353	33809	45888	56977	96625	155427
NMTTN	14303	27911	40919	57999	110429	187026
NMTTX	14724	27822	41015	59982	118971	203174
NMTUT	19594	36564	48970	64120	114238	192142
NMTVA	18110	37492	54412	73954	130744	200191
NMTVT	18846	34676	48801	64828	112505	176291
NMTWA	16911	33176	48706	67559	122304	195170
NMTWI	20197	35775	49327	65203	110653	174919
NMTWV	13208	24684	36090	49978	92711	147434
NMTWY	18171	32126	43820	57386	93773	145587

Bibliography

J. Abara. Applying Integer Linear Programming to the fleet assignment problem. *Interfaces*, 19(4):20–28, 1989.

Federal Aviation Administration. Airport Capacity Benchmark Report 2004. Report, Washington, DC, 2004).

L.A.N. Amaral and J.M. Ottino. Augmenting the framework for the study of complex systems. *The European Physical Journal*, 38:47–162, 2004.

R. Axelrod and L. Tesfatsion. A guide for newcomers to agent-based modeling in the social sciences, 2006. Available from `http://www.econ.iastate.edu/tesfatsi/abmread.htm`, October 2006.

G. Bamberger and D. Carlton. Airline networks and fares. *Handbook of Airline Economics*, pages 291–303, 2003.

C. Barnhart, N. Boland, L. Clarke, E. Johnson, G. Nemhauser, and R. Shenoi. Flight string models for aircraft fleeting and routing. *Transportation Science*, 32(3):208–220, 1998.

C. Barnhart, T. Kniker, and M. Lohatepanont. Itinerary-based airline fleet assignment. *Transportation Science*, 36(2):199–217, 2002.

M. Beckman. Decision and team problems in airline reservations. *Econometrica*, 26: 134–145, 1958.

P. Bell. Revenue management. Presentation slides, Richard Ivey School of Business, University of Western Ontario, 2005.

R. Bellmann. *Quarterly of Applied Mathematics*, 16:87–90, 1958.

P. Belobaba. Airline yield management: An overview of seat inventory control. *Transportation Science*, 21(2):63–73, 1987.

P. Belobaba. Application of probabilistic decision model to airline seat inventory control. *Operations Research*, 37(2):183–197, 1989.

F. Berardino. Integrating airline strategy and marketing. In *Handbook of Airline Marketing First Edition*, pages 105–116. 1998.

S. Berry, M. Carnall, and P. Spiller. Airline hubs: Costs, markups and the implications of customer heterogeneity. Paper NSF Grant SES-9122672, 1997. Available from `http://www.econ.yale.edu/~steveb/air.pdf`, October 2006.

M. Bierlaire. *Mathematical models for transportation demand analysis*. PhD thesis, Department of Mathematics, University of Namur (FUNDP), Namur, Belgium, 1996.

W. Black. *Transportation A Geographical Analysis*. The Guilford Press, New York, NY, 2003.

U. Blum and L. Dudley. Report of the 109th round table of transport economics. Transport and Economic Development, European Conference of Ministers of Transport", year = 2001, pages = "51-74", note = Available from `http://www1.oecd.org/publications/e-book/7502101E.PDF`, October 2006.

E. Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. Irvine, CA, 2002. National Academy of Sciences Adaptive Agents, Intelligence, and Emergent Human Organization: Capturing Complexity through Agent-Based modeling. Available from `http://www.icosystem.com/articles/scientific/PNAS2002.pdf`, October 2006.

S. Borenstein. The evolution of the U.S. airline competition. *Journal of Economic Perspective*, 6(2):45–73, 1992.

T. Botimer and P. Belobaba. Airline pricing and fare product differentiation: A new theoretical framework. *Operations Research*, 50:1085–1097, 1999.

E. A. Boyd. Revenue management and dynamic pricing. Presentation slides, PROS Revenue Management, Houston, TX, 2002.

M. Brooks and K. Button. Yield management: a phenomenon of the 1980s and 1990s? *International Journal of Transport Economics*, 21(2):177–196, 1994.

J. Brueckner and P. Spiller. Economics of traffic density in the deregulated airline industry. *Journal of Law and Economics*, 37:379–415, 1994.

J. Brueckner, N. Dyer, and P. Spiller. Fare determination in airline hub-and-spoke networks. *RAND Journal of Economics*, 23(3):309–333, 1992.

R. J. Brunner, K. Ramaiyer, A. Szalay, and A. J. Connolly. An object-oriented approach to astronomical databases. *ASP Conference Series*, 77, 1995.

M.J. Bruton. *Introduction to Transportation Planning*. Hutchinson Technical Education, London, 1970.

J. Carbonell, R. Michalski, and T. Mitchell. Machine learning: A historical and methodological analysis. *AI Magazine*, 4(3):69–79, 1983.

D. Caves, L. Christensen, and M. Tretheway. Economies of density versus economies of scale: Why trunk and local service airlines costs differ. *RAND Journal of Economics*, 15(4):471–489, 1984.

R. Chatwin. Continuous-time airline overbooking with time-dependent fares and refunds. *Transportation Science*, 33(2):182–191, 1999.

U. Cherubini and G. Della Lunga. *Structured Finance: The Object Oriented Approach*. John Wiley & Suns, West Sussex, England, 2007.

R. Cross. *Revenue Management: Hard-core tactics for market domination*. Broadway Books, New York, NY, 1997.

P. Davis. Airline ties profitability yield to management. *SIAM News*, 27(5), 1994.

A. Deardoff. The terms of trade and other wonders: Deardoff's glossary of international economics, 2006. Available from `http://www-personal.umich.edu/~alandear/glossary/`, June 2006.

D. DeLaurentis, C. Lim, and T. Kang. System-of-systems modeling for personal air vehicles. AIAA/ISSMO Symposium on Multidisplinary Analysis and Optimization.

D. DeLaurentis, C. Lim, and T. Kang. Approach to characterize mobility through modeling of solution spaces for conceptual air vehicles. *AIAA Journal of Aircraft*, 41(1):21–29, 2004.

R. Diestal. *Graph Theory 3rd Edition*. Springer-Verlag, New York, NY, 2005.

T. Dietterich. Machine-learning research; four current directions. *AI Magazine*, 18 (4):97–136, 1997.

E.W. Dijkstra. A note on two problems in connexion with graphs. *Numerische Mathematik*, 1:269–271, 1959.

E. Durfee and J. Rosenschein. Distributed problem solving and multi-agent systems: comparisons and examples. Contract report, University of Michigan, Ann Arbor, MI, 1994.

T. Eden, A. Knittel, and R. van Uffelen. Reinforcement learning. Lecture notes, School of Computer Science and Engineering, University of New South Wales", note = Available from `http://www.cse.unsw.edu.au/~cs9417ml/RL1/index.html`, October 2006.

W. Elmaghraby and P. Keskinocak. Dynamic pricing in the presence of inventory considerations Research overview, current practices, and future directions. *Management Science*, 49(10):1287–1309, 2003.

Energy Information Administration. World Crude Oil Prices, 2008. Available from http://tonto.eia.doe.gov/dnav/pet/pet_pri_wco_k_w.htm, September 2008.

J. Epstein and R. Axtell. *Growing Artificial Societies : Social Science From the Bottom Up*. MIT Press, Washington, DC, 1996.

Federal Aviation Administration. FAA Aerospace Forecast Fiscal years 2006-2017. Technical report, 2006a. Available from http://www.faa.gov/data_statistics/aviation/aerospace_forecasts/2006-20%17/, August 2006.

Federal Aviation Administration. Enplanements by Type of Carrier at Commercial Service Airports (Primary and Nonprimary) Extracted from the Air Carrier Activity Information System. Technical report, 2001. Available from http://www.faa.gov/airports_airtraffic/airports/planning_capacity/passe%nger_allcargo_stats/passenger/media/cy01_commercial_carrier.pdf, June 2006.

Federal Aviation Administration. FAA Previous Aerospace Forecasts. Technical report, 2006b. Available from http://www.faa.gov/data_statistics/aviation/aerospace_forecasts/, August 2006.

Federal Aviation Administration. Report to Congress: National Plan of Integrated Airport Systems (NPIAS) 2005 - 2009. Technical report, 2005. Available from http://www.faa.gov/airports_airtraffic/airports/planning_capacity/npias%/reports/media/NPIAS_Narrative.pdf, June 2006.

L.R. Ford. Network flow theory. Technical Report Paper P-923, The Rand Corporation, Santa Monica, 1956.

G. Gallego and G. van Ryzin. Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Management Science*, 40(8):999–1020, 1994.

N. Garber and L.A. Hoel. *Traffic and Highway Engineering*. Thomson Learning, 2001.

A. Garcia, E. Campon-Naez, and James Reitzes. Dynamic pricing and learning in electricity markets. *Operations Research*, 53(2):231–241, 2005.

A. Goetz and C. Sutton. The geography of deregulation in the U.S. airline industry. *Annals of the Association of American Geographers*, 87(2):238–263, 1997.

Richard Goodwin. Formalizing properties of agents. Paper CMU-CS-93-159, Pittsburgh, PA, 1993.

A. Gosavi. *Simulation-Based Optimization: Parametric Optimization Techniques & Reinforcement Learning*. Kluwer Academic Publishers, Norwell, MA, 2003.

A. Gosavi. A reinforcement learning algorithm based on policy iteration for average reward: Empirical results with yield management and convergence analysis. *Machine Learning*, 55:5–29, 2004.

M. Harmon and S. Harmon. Reinforcement learning: A tutorial. Technical report Task 2312R1, Wright Laboratory, Wright-Patterson AFB, 1996.

K. Hendricks, M. Piccione, and G. Tan. Entry and exit in hub-spoke networks. *RAND Journal of Economics*, 28(2):291–303, 1997.

J.H. Holland. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*. The MIT Press, Boston, 1992.

Housing and Household Economics Statistics. Number of earners–households, by total money income in 1995, type of household, presence of children, race, and hispanic origin of householder. Technical report, U.S. Census Bureau, 1995. Available from `http://pubdb3.census.gov/macro/031996/hhinc/6_001.htm`,.

S. Huang, D. Schleicher, and G. Hunter. Future flight demand generation tool. Chicago, Illinois, 2004. AIAA 4th Aviation Technology, Integration and Operations (ATIO) Conference.

A. Ilachinski. Irreducible semi-autonomous adaptive combat (isaac): An artificial-life approach to land combat. Research memorandum CRM 97-61.10, 1997. Available from `http://www.cna.org/isaac/crm9761.htm`, October 2006.

Integrated Decisions and Systems, Inc. The basic of revenue management. Report ID-MK-100102-v1-YMBasic, 2005.

D. Johnson. Transportation indicators. Technical report, U.S. Department of Transportation, Bureau of Transportation Statistics, 2002.

L. Kaelbling, M. Littman, and A. Moore. Reinforcement learning: A survey. *Journal of Artificial Intelligence Research*, 4:237–285, May 1996.

A. Kahn. The deregulatory tar baby: the precarious balance between regulation and deregulation, 1970-2000 and henceforward. *Journal of Regulatory Economics*, 21 (1):35–56, 2002.

K. Kansky. Structure of transportation networks: relationships between network geography and regional characteristics. Paper 84, Department of Geography, University at Chicago, 1963.

S.A. Kauffman. *The Origins of Order: Self-Organization and Selection in Evolution*. Oxford University Press, New York, 1993.

S. Kimes. Yield management: a tool for capacity-constrained service firms. *Journal of Operations Management*, 8(4):348–363, 1989.

M. Laguna. Revenue management. Lecture slides, Leeds School of Business, University of Colorado at Boulder, Boulder, CO, 2004.

J. Lewe. *An Integrated Decision-Making Framework for Transportation Architectures: Application to Aviation Systems Design*. PhD thesis, School of Aerospace Engineering, Georgia Institute of Technology, Atlanta, GA, 2005.

C. Lim, J. Lewe, and D. Mavris. An agent-based modeling approach for transportation network systems. Wichita, KS, 2006. AIAA Aviation Technology, Integration and Operations (ATIO) Conference.

C. Lim, J. Lewe, and D. Mavris. An agent-based approach for modeling the commercial air transportation network system. Berkeley, CA, 2007. Air Transport Research Society (ATRS) World Conference.

K. Littlewood. Forecasting and control of passenger bookings. pages 95–117. AGIFORS Symposium, 1972.

M. Loyalka. Your air taxi is almost ready. *Business Week Online*, September 2005. Available from `http://www.businessweek.com/smallbiz/content/sep2005/sb20050916_272956.%htm`, October 2006.

R. McAfee and V. te Velde. Dynamic pricing in the airline industry. Paper, California Institute of Technology, Pasedena, CA, 2004.

M. McNally. The Four Step Model. Paper UCI.ITS.AS.WP.00.5, Center for Activity Systems Analysis, University of California, Irvine, Irvine, CA, 2000).

E.F. Moore. The shortest path through a maze. In *Proceedings of the International Symposium on the Theory of Switching*, pages 285–292. Harvard University Press, 1959.

H. Morowitz. *The Emergence of Everything : How the World Became Complex*. Oxford University Press, New York, NY, 2002.

S. Morrison and C. Winston. Airline deregulation and public policy. *Science*, 245 (4919):707–711, 1989.

Y. Narahari, C. Raju, K. Ravikumar, and S. Shah. Dynamic pricing models for electronic business. *Sadhana*, 30(2 & 3):231, 2005.

NASA. *NASA Aeronautics Blueprint: Towards a Bold New Era in Aviation*. Aeronautics Research Mission Directorate, 2002. Available from `http://www.aero-space.nasa.gov/tf/aero_blueprint/index.html`, February 2006.

National Research Council. *Decadal Survey of Civil Aeronautics: Foundation for the Future*. Aeronautics and Space Engineering Board, 2006. Available from `http://newton.nap.edu/catalog/11664.html`, August 2006.

W. Niedringhaus. An agent-based model of the airline industry. Technical report, MITRE Corporation, McLean, VA, 2000.

W. Niedringhaus. The Jet:Wise model of National Airspace System evolution. *Simulation*, 80(1):45, 2004. The Society for Modeling and Simulation International.

N. Nilsson. *Introduction to Machine Learning (draft)*. Stanford, CA, 1996. Available from `http://ai.stanford.edu/people/nilsson/mlbook.html`, October 2006.

J. Odell, H. Parunak, M. Fleisher, and S. Brueckner. Modeling agents and their environment. Technical paper Volume 2585, Springer, Berlin, 2002.

Office of Advocacy. Rural and urban areas by firm size, 1990-1995. Technical report, U.S. Small Business Administration, 1999. Available from `http://www.sba.gov/advo/stats/urb_rur.pdf`,.

Office of Economic Affairs, Economic, and Market Analysis Division. 1999 & estimated 2005 decile distributions of family income by metropolitan statiscal areas and non metropolitan counties. Technical report, U.S. Department of Housing and Urban Development, 2005. Available from `http://www.huduser.org/datasets/il/il05/Medians_2005.doc`,.

Omnibus. Airline passenger travel. Technical report, U.S. Department of Transportation, Bureau of Transportation Statistics, 2003.

E. Perez and M. Trottman. Major airlines fuel a recovery by grounding unprofitable flights. *The Wall Street Journal*, June 2006.

S. Peterson and I. Harrington. Overview of the travel demand forecasting methodology. Report, Central Transportation Planning Staff (CTPS), Reston, VA, 2008).

Raytheon ACES team. Airspace Concept Evaluation System (ACES) software user manual. Technical report, Raytheon Company, Marlborough, MA, 2005.

D. Reed. World airline industry recovering. *USA Today*, page 5b, 2006.

D. Renner. Supply and demand: The market mechanism. Available from `http://krypton.mnsu.edu/~renner/supdem.htm`, June 2006.

C. Reynolds. Individual-based models, 1999. Available from http://www.red3d.com/cwr/ibm.html, June 2006.

J. Rodrigue, C. Comtois, and B. Slack. *The Geography of Transport Systems: Transport Geography on the Web*. Routledge, 2006. Available from http://people.hofstra.edu/geotrans/index.html, Jan 2006.

J. Rosenberger, E. Johnson, and G. Nemhauser. A robust fleet-assignment model with hub isolation and short cycles. *Transportation Science*, 38(3):357–368, 2004.

K. Roth and R. Miraflor. ACES fact sheet. NASA Ames Research Center, 2004. Available from http://vams.arc.nasa.gov/activities/aces.html, April 2006.

RTI International. Monte Carlo Air Taxi Simulator (MCATS), 2006. Available from http://www.rti.org/page.cfm?objectid=2D2F254F-9700-45D2-836A03454631259%0, July 2006.

A. Samuel. Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development*, 3:210–229, 1959.

R.G. Sargent. Verification, validation, and accreditation of simulation models. 2000 Winter Simulation Conference, 2000.

R. Schwab, A. Haroldsdottir, P. Kostiuk, and R. Simpson. A preliminary design process for airspace systems initial assessment, chicago case study report. Final report VNTSC-DTS20-PDP-001, Volpe National Transportation Systems Center, 2000.

M. Schwind and O. Wendt. Dynamic pricing of information products based on reinforcement learning: A yield-management approach. Aachen, Germany, 2002. 25th Conference on Artificial Intelligence.

P. Stone and M. Veloso. Multiagent systems: A survey from a machine learning perspective, 1997.

R. Sutton and A. Barto. *Reinforcement Learning: An Introduction*. MIT Press, Cambridge, MA, 1998.

D. Sweet, V. Manikonda, J. Aronson, and K. Roth. Fast-time simulation system for analysis of advanced air transportation concepts. Monterey, CA, 2002. AIAA Modeling and Simulation Technologies Conference and Exhibit.

K. Talluri. Swapping applications in a daily airline fleet assignment. *Transportation Science*, 30(3):237–248, 1996.

R. Tankelevich. Artificial intelligent. Lecture notes, Department of Mathematics and Computer Science, Colorado School of Mines, 2006. Available from `http://www.mines.edu/~rtankele/cs404/index.htm`, October 2006.

E. Tatara, M.J. North, T.R. Howe, N.T. Collier, and J.R. Vos. An introduction to repast modeling by using a simple predator-prey example. Argonne, IL, 2006. Agent 2006 Conference on Social Agents: Results and Prospects.

C. Taylor. The determination of passenger booking levels. pages 93–116. AGIFORS Symposium, 1962.

K. Taylor. *Human Society and the Global Economy*. 1996. Available from `http://distance-ed.bcc.ctc.edu/econ100/ksttext/chaplist.htm`, Jan 2006.

P.J. Taylor. *Quantitative Methods in Geography*. Waveland Press, Prospect Height, IL.

G. Tesauro. Practical issues in temporal difference learning. *Machine Learning*, 8: 257–278, 1992.

G. Tesauro. Temporal difference learning and td-gammon. *Communications of the ACM*, 38(3):58–68, 1995. Available from `http://www.research.ibm.com/massive/tdl.html#ref10`, October 2006.

H. Thompson. Statistical problems in airline reservation control. *Operationgs Research Quarterly*, 12:167–185, 1961.

M. Toniolo and J. Brindel. Monte Carlo Air Taxi Simulator program user's guide v2.5. Technical report, RTI International, McLean, VA, 2005.

A. Trani. System models for the NAS strategy simulator. Washington, DC, 2006. NEXTOR Research Seminar.

A. Trani, H. Baik, and S. Ashiabor. An integrated model to study the Small Aircraft Transportation System. *Transportation Research Record 1850, National Research Council*, pages 1–11, 2004.

U.S. Census Bureau. Number of firms, number of establishments, employment, annual payroll, and receipts by employment size of the enterprise for metropolitan statistical area, major industries - 1997. Technical report, U.S. Census County Business Patterns, 1997.

U.S. Department of Transportation. The 1995 American Travel Survey. Bureau of Transportation Statistics, 1999. Microdata CD-ROM.

M. Waldrop. *Complexity: The Emerging Science at the Edge of Order and Chaos*. Touchstone Simon & Schuster Inc., New York, NY, 1992.

F. Wallenberg. A study of airline pricing. Paper, University of California at Berkeley, Berkeley, CA, 2000.

D.J. Watts and S. Strogatz. Collective dynamics of 'small-world' networks. *Nature*, 393:440–442, 1998.

L. Weatherford. EMSR vs. EMSU: revenue or utility? Honolulu, HI, 2003. Agifors Yield Management Study Group. Presentation Slides.

E. Weiner. Urban transportation planning in the united states: An historical overview. Technical Report 5th Edition, Washington, DC, 1997.

E. Yang, J. Lewe, and D. Mavris. Demand-centric analysis of the air transportation system. Anchorage, Alaska, 2008. AIAA 8th Aviation Technology, Integration and Operations (ATIO) Conference.

L. Yang and R. Kornfeld. Examination of the hub-and-spoke network: A case example using overnight package delivery. AIAA 41st Aerospaces Sciences Meeting and Exhibit, 2003.

C. Zhong. *Modeling of Airport Operations Using an Object-Oriented Approach*. PhD thesis, Virginia Tech, Blacksburg, VA, 1997.

VITA

Choon Giap Samson Lim was born in Malacca City, Malaysia to Mr. Victor Lim and Ms. Anne Ngong. He resided in Malaysia for his first 20 years before coming to the United States of America to attend the SUNY at Buffalo from January 1999 to May 2001. After graduating with a Bachelors of Science in Aerospace Engineering, he moved to Atlanta, Georgia to attend graduate school at Georgia Tech. He graduated with a Masters of Science in Aerospace Engineering in December 2003 and while pursuing his Ph.D. studies, he also graduated with a Masters of Business Administration in May 2006. Since joining the Aerospace Systems Design Laboratory at Georgia Tech in August 2001, his research endeavors included personal air vehicles, system-of-systems research, and agent-based modeling and simulation before narrowing down to airline economics and air transportation system modeling and simulation for his Ph.D. research.